THE EFFECT OF BLENDED MASSIVE OPEN ONLINE COURSES ON STUDENTS' PERCEPTIONS OF THEIR ENGAGEMENT AND LEARNING OUTCOMES

By

John Kwame Eduafo Edumadze

Student Number - 219091722

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Supervisor: Prof. Desmond W. Govender

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DECLARATION

Submitted in fulfilment / partial fulfilment of the requirements for the degree of

Doctor of Philosophy, in the Graduate Programme in **Computer Science Education**,

University of KwaZulu-Natal, Pietermaritzburg, South Africa.

I, **John Kwame Eduafo Edumadze**, declare that:

1. The research reported in this thesis, except where otherwise indicated, is my original research.
2. This thesis has not been submitted for any degree or examination at any other university.
3. This thesis does not contain other persons' data, pictures, graphs or other information, unless specifically acknowledged as being sourced from other persons.
4. This thesis does not contain other persons' writing unless specifically acknowledged as being sourced from other researchers. Where other written sources have been quoted, then:

a. Their words have been re-written, but the general information attributed to them has been referenced.

b. Where their exact words have been used, then their writing has been placed in italics and inside quotation marks and referenced.

5. This thesis does not contain text, graphics or tables copied and pasted from the Internet, unless specifically acknowledged, and the source being detailed in the thesis and in the References sections.

John Kwame Eduafo Edumadze

October 2023

[redacted]

Prof. Desmond W. Govender

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DEDICATION

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ABSTRACT

Massive open online courses (MOOCs) have arisen in recent years and have sparked significant discourse regarding education. MOOCs have become firmly established in the educational landscape and have undergone various adaptations, including the emergence of blended MOOCs integrating campus-based courses with MOOCs, resulting in a more profound learning experience. Blended MOOCs enable the use of various blended pedagogies, which can be used to offset the numerous challenges facing higher education in the global south, such as 1) limited access, 2) inadequacies and obsolescence infrastructure, 3) limited resources, 4) students' enrolment that is far beyond what they were designed to accommodate, 5) overcrowding in lecture halls, 6) shortage of lecturers, especially research-active and experienced senior academics, 7) poor quality of education to meet the needs of today's workforce and 8) mismatch between the skills of graduates. This study examines how blended MOOCs relate to students' learning and perceived academic performance. It analyses students' acceptance and use, engagement, and factors influencing their satisfaction and perceived academic performance. This analysis incorporates the revised Community of Inquiry (CoI) framework, including learning presence and the extended Unified Theory of Acceptance and Use of Technology (UTAUT 2) models. An empirical study was conducted with 2875 students from the University of Cape Coast, Ghana, selected via two-stage cluster sampling to accomplish this objective. The respondents were levels 100, 200, 300 and 800 students who were instructed to enrol into MOOCs as open educational resources (OERs) to supplement their campus-based for a semester. Upon the conclusion of the semester, the students were requested to complete a questionnaire. Subsequently, the collected data underwent analysis utilising SmartPLS v4 and SPSS v28 software. In general, the model demonstrates a strong alignment with the gathered data and possesses an adequate level of efficacy in elucidating the phenomenon of students' usage acceptance (UTAUT 2) of blended MOOCs and its impacts on engagement (CoI), satisfaction and academic performance. The findings have several implications for research and EdTech integration practices among sub-Saharan nations, which were also discussed. Consequently, this study offers significant contributions to the theory and practice of active learning in a blended MOOC environment.

Keywords: *Blended MOOCs, Students Engagement, Academic Performance, Community of Inquiry, Unified Theory of Acceptance and Use of Technology.*

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CHAPTER 1:BACKGROUND AND CONTEXT

1.1 Introduction

Nations in the global south are lagging far behind their counterparts in the global north regarding socio-economic and developmental indicators. The chief reason is lack of education (Trefzer et al., 2014), which is unaffordable, inaccessible and outmoded–lacking technological mediation. Quality education, especially at the tertiary level that included increased access to science, technology and innovation, leading to a top level of growth and productivity, holds the key to the transformation. The significance of education is shown in the inclusion of education-related themes in both millennium development goals (MDGs) and sustainable development goals (SDGs), that succeeded the MDGs. An example of this can be seen in the fourth Sustainable Development Goal (SDG), which wishes to guarantee an inclusive and equitable provision of high-quality education while fostering lifelong learning opportunities for individuals of all backgrounds. The person and society profit from education because of the positive correlation between higher education and development, which drives economic growth and fortifies essential public services (Schendel & McCowan, 2016). In this respect, the erstwhile MDGs, for instance, urged African governments to focus on improving national literacy since it is the surest way of relieving the continent of poverty and ushering in the needed development. About 40% of Africa's population was under the age of 15 years in 2022, compared to 25% globally (Galal, 2023). For this reason, with proper education and training at the tertiary level, the youth of Africa could be built into an educated and highly skilled workforce capable of propelling the continent from abject poverty and starvation into food sufficiency, economic independence, development and advancement. The returns to schooling are highest in Sub-Saharan Africa (Psacharopoulos & Patrinos, 2018), with Africa having the world's highest returns to investments in higher education, which is 12.5 per cent (Patrinos, 2016)). Aside from the above reason for the demand for higher education in Africa, United Nations Educational, Scientific and Cultural Organization (UNESCO) hinted that globally, this demand is fuelled by several factors, among which are:

- There has been a significant increase in the number of elementary and secondary school students over the past decade, indicating that there will soon be a large number of people seeking higher education.

- The opportunities and demands of the globalised economy have made lifelong learning much more necessary.

Tertiary education helps economies catch up to more technologically sophisticated cultures because graduates have a greater familiarity with and ability to use emerging technologies. (Bloom et al., 2014). However, as depicted by Table 1-1, in 2020, only 9.8% of young people in sub-Saharan Africa (SSA) , which includes Southern and Eastern Africa and Western and Central Africa, are enrolled in higher education institutions, while the global average is 40.3% (Darvas et al., 2017; Mohamedbhai, 2011, 2014).

Table 1-1:Gross Tertiary Enrolment Ratio (GTER) by World Region: 1970-2020 in percentages.

World Region	**Years in Decade**					
	1970s	**1980s**	**1990s**	**2000s**	**2010s**	**2020**
East Asia and the Pacific	5.1	7.3	10.8	17.7	38.0	51.0
EU	23.2	27.4	37.4	50.1	66.0	75.1
Europe and Central Asia	28.2	32.6	42.7	55.8	68.2	76.3
Latin America and Caribbean	13.1	15.2	19.4	27.6	44.5	54.4
Middle East and North Africa	8.5	10.9	15.8	24.5	37.9	41.0
North America	54.4	61.6	76.0	81.8	86.5	86.8
South Asia	5.7	6.6	10.3	14.3	22.0	25.8
Southern and Eastern Africa	2.3	2.9	3.3	4.1	5.9	6.3
Sub-Saharan Africa	1.6	2.6	3.7	5.9	8.9	9.8
Western and Central Africa	0.9	2.2	3.7	6.8	9.2	10.2
World	11.0	13.0	15.5	23.5	34.2	40.3

Source. World Bank (2023).

Both **Error! Reference source not found.** and **Error! Reference source not found.** reveal a noticeable pattern. The differences in the tertiary enrolment rates in sub-Saharan Africa during the 1970s were less massive than those in other developing regions such as East Asia and the Pacific, the Middle East and North Africa, and South Asia. Nevertheless, a notable disparity emerged between 1990 and 2020, with Sub-Saharan Africa falling behind these regions regarding tertiary enrolment rates. The increasing disparity gives rise to concerns regarding the region's capacity for innovation and its competitiveness on a global scale. Given the discrepancies mentioned earlier, the research underscores the critical nature of confronting the issue of inadequate tertiary enrolment in African nations. An area that shows promise for intervention is the investigation of novel approaches, specifically within the domain of Education Technology (EdTech).

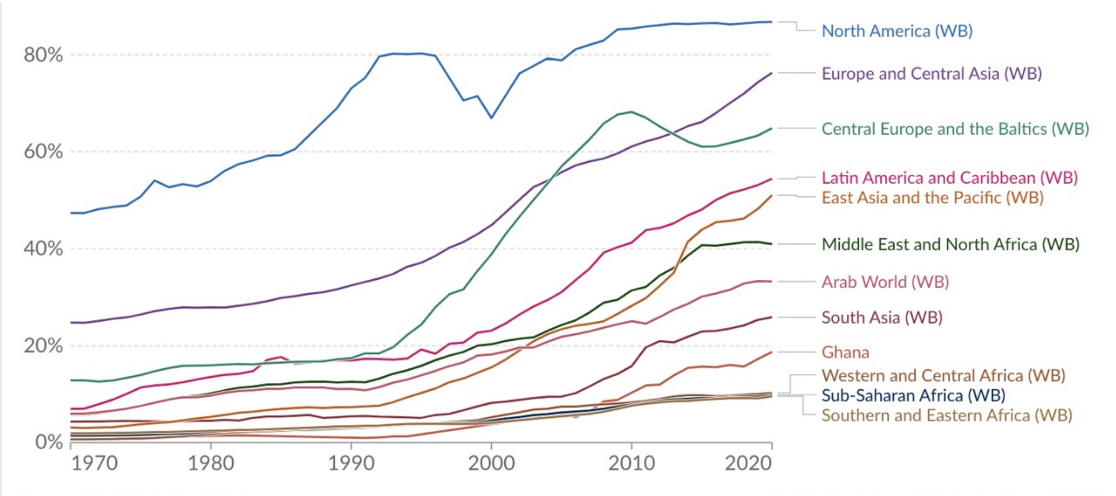

Figure 1-1.Gross Tertiary Enrolment Ratio (GTER) by World Region: 1970-2020.

Source. World Bank (2023).

However, the flip side of Table 1.1 and Figure 1.1 by World Region: 1970-2020 tells a different story: enrolment into tertiary education in sub-Saharan Africa shows a positive change. Some of the pieces of evidence are indicated in the paragraph below:

- The Gross Enrolment Ratio (GER) or Gross Tertiary Enrolment Ratio (GTER) rose at a pace of 2.8% per year globally between 1970 and 2013, whereas it climbed at a rate of 4.3% per year in Sub-Saharan Africa (Darvas et al., 2017; Marginson, 2016).
- The number of students enrolled in colleges and universities has increased by over 200 per cent from 2.3 million in 2000 (Africa-America Institute(AAI), 2015; Marginson, 2016).

Nevertheless, gains in enrolment have not met rising demand as countries in SSA are under increasing pressure to expand access to higher education (Alcorn et al., 2015; Darvas et al., 2017; Mohamedbhai, 2011). Table 1-1 shows that in 2020, the global GTER average was 40.3%. While it was highest in North America (86.8%), it was lowest in Southern and Eastern Africa (6.3%), which is part of Sub-Saharan Africa (9.8%). Though Ghana, the focus of this study, has had her GTER above that of SSA as shown in Figure 1-2, it is still not good enough, making any call to investigate strategies to increase GTER legitimate and very important. The GTER of Ghana in 2020 was 18.69 per cent– an increase from 11.77 per cent in 2011 – an average annual rate change of 7.61 per cent, as shown in Figure 1-2. Ghana's GTER needs to increase further to match her lower-middle-income status and her desire to participate actively in the knowledge economy portray in ICT for accelerated development agenda (ICT4AD) (Ghana ICT4AD,2003).

Year	GER (%)	Change (%)
1971	**0.69**	-
1972	0.74	6.52
1973	0.81	10.46
1974	0.94	15.76
1975	0.99	5.13
1976	1.09	9.59
1982	1.50	38.16
1991	0.92	-38.47
1992	1.06	14.76
1993	1.26	18.56
1994	1.28	1.81
2005	5.87	359.47
2006	5.24	-10.67
2007	6.44	22.94
2008	8.48	31.60
2009	8.80	3.75
2011	11.77	33.87
2012	11.94	1.48
2013	13.83	15.82
2014	15.40	11.35
2015	15.69	1.87
2016	15.54	-0.98
2017	16.01	3.07
2018	15.69	-2.01
2019	17.23	9.82
2020	18.69	8.44

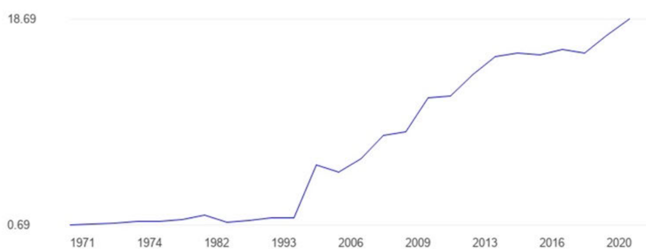

Figure 1-2. Ghana gross enrolment (GER) in tertiary education from 1971-2020.

*Source***.**TheGlobalEconomy.com. (2023).

Ghana's educational system faces a significant obstacle: only 20% of eligible candidates can enter its universities (TheGlobalEconomy.com, 2023). Approximately 80% of aspiring students need access to further education, impeding their potential for transformation. When students are not allowed to enter, they are compelled to pursue other options, which can result in them being underemployed, having limited career opportunities, and perpetuating societal disparities (Donkor, 2021). Ponelis and Holmner (2015) made these comments on the need for research to focus in digital transformation through education.

> ICT research in Africa has shifted its focus from bridging the digital divide to transforming societies and economies by enhancing digital opportunities and social inclusion. The importance of using ICTs for capacity-building are empowerment, governance, social participation, scientific research, information sharing, cultural creations, performances, and exchanges of knowledge, and enhancing learning opportunities. The barriers to overcome are no longer only technological but also educational, cultural and linguistic in nature. Neglecting to invest sufficiently in human capacity by educating African may result in the "last mile" challenge becoming the "lost mile".

The restricted availability of higher education affects individual ambitions and presents complex obstacles to national progress. The repercussions of this restricted access are diverse and extensive. Studies have identified some of these repercussions, which are highlighted in the next paragraphs.

Effects on Students:

1) Missed opportunities: When students are denied entry to university, they are compelled to follow alternate pathways that may not correspond with their talents and desires. These circumstances can result in inadequate employment, reduced opportunities for advancement, and a feeling of unrealised potential (Chan, 2016, Chen. 2023).
2) Economic disadvantage: The absence of knowledge and skills obtained from tertiary education restricts people's opportunities for higher-paying employment, perpetuating poverty cycles and impeding national economic progress (Chamorro-Premuzic & Frankiewicz, 2019; Chen. 2023; Schendel & McCowan, 2016).
3) Social disparities: The restricted availability of university education worsens pre-existing societal inequities, disproportionately affecting students from disadvantaged families who depend on higher education to improve their social and economic status (Chan, 2016; Chamorro-Premuzic & Frankiewicz, 2019).

Effect on the progress and advancement of a nation:

1) Untapped potential: Ghana's failure to educate and empower a substantial section of its youth population deprives the country of a crucial reservoir of talent and skills necessary for national progress (Donkor, 2021).
2) Shortage of trained labour: A need for more university graduates might result in a deficiency of proficient specialists in crucial industries, impeding the process of economic diversification and modernisation (Chan, 2016).
3) Brain drain: Highly skilled students may pursue educational and career prospects outside, exacerbating Ghana's depletion of human resources (Campus France, 2020).

Most SSA governments have not been able to provide the needed educational infrastructure, including educational technology (EdTech), to modernise their educational system and take advantage of its effectiveness and efficiency, thus enhancing the quantity and quality of education delivery (African Development Bank, 2020; Lillian, 2021; Rivers et al., 2015). According to Campus France (2020), 1) globalisation, 2) political and economic instability and 3) underfunded and unevenly subsidised higher education systems all contribute to student mobility in sub-Saharan Africa. Campus France (2020, para. 12) further characterised the universities in SSA as "higher education systems that are underfunded", while Kigotho (2020, p.5) said they are "under-funded local public universities". In furtherance to the call for an effective learning system, United Nations Educational, Scientific and Cultural Organization (UNESCO) encouraged developing member states to formulate national education policies to respond to the dynamic needs of their populations for access to high-quality education, innovation, and research (Rodriguez & Dieker, 2018). Since the call has been slow in its implementation, the upsurge in demand for tertiary education has exposed the hidden problems that most universities in SSA are facing, which are infrastructure deficiencies, inadequacies, obsolescence, limited resources (Amnesty International, 2020; McCowan, 2018; Mohamedbhai, 2011; UNESCO, 2010) with some researchers describing the existing infrastructure as crumbling infrastructure (Amnesty International, 2020; Sasu, 2021) and precarious infrastructure (McCowan, 2018). Moreover, there is a shortage of lecturers (Amazan, 2021; Mohamedbhai, 2011; Trines, 2018). Since most African public institutions enrol significantly more students than intended (Mohamedbhai, 2011), this poses a severe problem. Ghanaian universities can accommodate only around 20% of those who apply International Consultants for Education and Fairs (ICEF Monitor, 2020). Further increase in in-take has resulted in the following effects:

- Unfortunately, at some African colleges, overcrowding of lecture halls has become the norm (AAI, 2015; Jouicha et al., 2020, p.1747; Luescher & Klemenčič, 2017, p.117; Materu et al.,2011, p.169).
- Shortage of lecturers, especially research-active and experienced senior academics (Amazan, 2021; Asamoah & Mackin, 2015; Mohamedbhai, 2011), leads to an increased workload. African colleges have 50% more students than the worldwide average (Africa-America Institute, 2015; Amazan, 2021).
- Subpar education that fails to satisfy the demands of today's workforce, with potential employers often dissatisfied with the skills and quality of graduates (Kigotho, 2018) as lecturers are overwhelmed with academic load, thus affecting supervision. The quality of African higher education has been on the decline since the 1908s (Shabani et al., 2014).
- There is a severe mismatch between the skills/education of graduates and the demands of a local and global workforce for available jobs/occupations (Africa-America Institute, 2015; Kigotho, 2018) leading to graduate unemployment and lack of well-paid jobs. Courses are mounted based on what academic staff can teach and not on the market-driven demands.
- Wealthy students seek education abroad because of the above. It has been estimated that approximately 5% of the 8.1 million university students in Sub-Saharan Africa study abroad. African students are the world's most mobile tertiary students, with 374,425 crossing borders in 2017, a 26% increase from 296,395 in 2012(Campus France, 2020; Kigotho, 2020). This 5% annual migration of Africa students abroad is way above the 2.4% global average. The indicators imply that the SSA outbound student population will grow, reaching 22 million by 2027 (Campus France, 2020; Kigotho, 2020). The number of Ghanaian students at the tertiary level studying abroad climbed from 9,329 in 2010 to 17,212 in 2019–an 84.5 per cent increase (Sasu, 2021). This is a conservative estimate, given that there are at least 7,000 studying in China alone (ICEF Monitor, 2020). According to ICEF Monitor (2019), Sub-Saharan Africa will soon be a hot spot for the next wave of student migration due to its large college-aged population. Ghana, among

other countries, like Angola, Cameroon, DRC, Ethiopia, Kenya, Nigeria, Rwanda, South Africa, and Zimbabwe, are the spotlight of this outbound student's mobility (Kigotho,2020).

If not overcome, these challenges will hamper African nations' industrialisation, advancement and globalisation drive and their drive-in participation in the knowledge economy. Higher education and research and development are the bedrock of the desirables mentioned above, meaning the demand for higher education enrolment will not abate. The need for increased enrolment and its associated challenges is a double-bind situation that needs fixing.

Regarding capital investment to offset the infrastructure deficiency to meet the demand for higher education in Africa, Experton and Fevre (2010) hinted that the ability to support an increased supply of postsecondary education in SSA needs to catch up to the rising demand. For Africa to meet its higher education needs over the next decade and a half, it would need to construct ten universities every week and enrol 10,000 students, as per some estimations. (Kigotho, 2018; Parr; 2017; Trines, 2018). This suggestion is akin to what happened in the USA and India, where an average of one new community college was built weekly, and six new colleges were built daily in the 1960s and 2000s (Alcorn et al., 2015, p.43). Even if the above is conceivable, the number of individuals (high-quality teachers and school administrators) who can meet these students' needs is not increasing fast enough to keep up with the rising number of students (Alcorn et al., 2015). The suggestion is a high demand that is impossible to meet as the education sector of most African countries has the lion share of budgetary allocation. One of the reasons for high tertiary enrolment rates in the global north is that new technologies are considered as the driving force behind rising college enrolment rates (Altbach et al., 2019).

The solution is not in the traditional way of delivering education, as it should be partly responsible for the problem in the first place. There should be a paradigm shift in education delivery that is easily scalable to meet the increasing demands of tertiary education in SSA. These are the reasons why it has been highlighted that African governments should include online education as part of the solution in meeting the increasing demand of tertiary education in Africa (Kigotho, 2018; Parr, 2017). Online education is an equally effective but modern and much cheaper alternative means of education in an era where there is a proliferation of the internet and mobile computing.

Online learning stands out among other alternatives such as open and distance learning (ODL) and private universities (Mohamedbhai, 2011). In a rapidly changing global economy characterised by various uncertainties and dynamic cultural integration, putting a price tag on having a sound learning management system (LMS) in a university setting is challenging (Debroux, 2017). Learning in the 21st century goes beyond the exchange of knowledge and information between a teacher and a student but requires a conducive medium for effective interaction and participation of the two in the exchange process (Bolisani & Bratianu, 2017). As a result of the need for interaction between instructors and learners, many educational institutions worldwide are adopting and integrating LMS into teaching strategies (Cooper & Sommer, 2018). Bralić and Divjak (2018) advocate that such LMS must use modern technology to create a careful blend of traditional and modern teaching and learning strategies. Though most developed countries have enacted policies to encourage the adoption of LMS in higher education, the problem is that the pace has been remarkably slow in less developed places like South America, South Asia, and especially Africa (Mestry, 2017).

The pressing nature of tackling the 80% lack of access to tertiary education in Ghana and most countries in SSA and its vast ramifications require new solutions. Online learning such as Massive Open Online Courses (MOOCs) have the potential to significantly change the way access to high-quality education is distributed, making it more accessible to a broader audience. MOOCs, which are flexible, affordable, and of excellent quality, can complement conventional university education or provide an alternate route, providing hope to the 80% presently excluded. Furthermore, MOOC is capable of solving most of the challenges enumerated above, which is not peculiar to only SSA but the whole of the global south and thereby aiding in achieving the SDG 4, especially with affordability and accessibility of mobile computing devices and internet in this part of the world (Rambe & Moeti, 2017). Writing on the deployment of MOOC in Russia – a developed economy, Larionova and colleagues (2018) stated:

> the use of MOOCs in Russia to promote university-level delivery of educational programmes opens up opportunities in terms of widening student education options, developing virtual academic mobility, reducing the cost of educational services and enhancing access to education (Larionova et al., 2018).

If the aforementioned benefits can be accrued to a country like Russia, how much more could MOOC, once fine-tuned can, help in the modernisation of education of countries in the global south as well as bringing up “affordable”, job-oriented and highly demanded education to all who are willing to learn. Hitherto, learners were challenged in accessing such quality educational resources; however, with MOOCs, learners anywhere, anytime and anyhow can access such rich and high-quality educational resources without any restriction. India's government is using MOOCs— with the ability to expand with little additional expense —to meet the increasing but unmet demand for higher education and professional training (Alcorn et al., 2015). Since MOOCs offer instructional materials such as lesson plans, textbooks, and pedagogical techniques that are unavailable locally, they play a function comparable to that of open education resources (OERs) in influencing the agendas of higher education sectors in developing countries (D'Antoni, 2008). MOOC has been considered a potentially disruptive technology, changing how education is done, especially lifelong learning. A new higher education ecosystem can develop in the global south if traditional university courses are combined with high-quality MOOCs provided by universities worldwide. (Alcorn et al., 2015). In this respect, through MOOC, learners from the global south in general and Ghana specifically can have a ‘taste’ and ‘feel’ of the education of the global north, leading to possibly a narrowing of the gap–digital, technological knowledge, education, social, economic and political–among them. Again, it will minimise the considerable cost incurred by Ghanaian students to study abroad due to the inability of Ghanaian universities to offer certain courses in some programmes or whole programmes. For Ossiannilsson et al. (2016), MOOCs should be considered as a natural part of universities' course offerings and business models and should be recognised as valuable educational resources for learners in-take either at their university or from other providers. Higher education in most developed countries in the West and across Asia have used online learning management systems to increase enrolment and meet the needs of students who cannot leave their home communities (Kesselman et al., 2018). The shift from closed, campus-based courses to open, online ones is partially facilitated by MOOCs (Ossiannilsson et al., 2016), which are pedagogical innovations and change agents. The adoption of technology has not only made education more ubiquitous but has retained and/or improved the quality of education (Collins & Halverson, 2018). Similarly, it has been indicated that India and China are gradually becoming the leading nations in digital education due to the enormous use of the MOOC system (Alcorn et al.,2015). As the most innovative online learning system, MOOCs are new education paradigm for anyone, anywhere, anytime, using any computing device.

MOOCs significantly influence both the environments outside and inside universities, particularly for a traditional university focused on brick-and-mortar (Cabral, et al., 2016).

One such influence is how MOOCs are changing the instructional delivery of traditional classrooms, where a blend of the two has been formed. The blending of in-classroom sessions of a course with a MOOC is variously referred to as "distributed flip", "blended/hybrid model", "blended MOOC"(Almutairi and White, 2018); “glonacal” MOOC (Norberg et al., 2015) or bMOOC (Yousef et al., 2015). In other words, blended MOOCs mean MOOCs embedded in traditional face-to-face (F2F) courses. Replaying lectures, supplementing or replacing secondary materials, bridging knowledge gaps, exposing students to different teaching and discussion methods, practising and perfecting essential skills, and learning how to learn online are just some of the many advantages of online learning (Brali & Divjak, 2018; Griffiths et al., 2015). The most significant time may be available for in-class discussions, practical exercises, and collaborative projects when MOOC components are incorporated into traditional lectures (Wu & Chen, 2017). To improve efficiency, universities could implement such a plan by encouraging professors to spend less time lecturing on material that has mostly stayed the same and more time interacting with individual students to help them learn the material (Fox, 2013). The after-effect of such a blend is to maximise the leverage of the scarce resource of the instructor’s time (Fox, 2013). Although blended MOOCs have now become a more “advanced and sophisticated delivery of content” form of e-learning, they are still not popular in the developing world (Altbach, 2014; Ma & Lee, 2019). For the African continent to be able to catch up with the rest of the world, MOOCs or blended MOOCs could be the way to meet SDG 4 goals. However, such a conclusion cannot be made without comprehensive studies to know whether blended MOOCS would fit into African students' lives as learners from different cultures behave differently when using educational systems (Clarke, 2002; Liu, et al., 2016). In this respect, African students' readiness, perceptions, acceptance, satisfaction and experiences with this system and strategy of instructional delivery mode are worthwhile to aid management's future adoption decision. Moreover, by the diffusion of innovation (DoI) theory (Rogers, 2010), technological innovation goes through five stages: awareness, interest, evaluation, trial, and adoption. Thus, the use of blended MOOCS so far can be considered the trial stage in Ghana. An assessment of such an innovative system at the trial stage is necessary before its adoption.

For Halverson et al. (2014), blended learning experiences include outcomes like how well students do (student performance), how satisfied they are (student satisfaction) and their opinions on improving the teaching-learning method. (a guide to its future designs (Halverson et al., 2014). The MOOCs that are the target of this research are the ones created by individual universities or corporations, which are accessible by anyone freely. However, for this research, students were asked to register and use as open educational resources (OERs) to supplement the delivery of another university's course. The benefits of blended MOOCS are optimising student engagement, satisfaction, and, ultimately, learning (Bruff et al., 2013).

One of the advantages of blended MOOCs is that they improve the level of students' engagement (Almutairi & White, 2018; Guo et al., 2014; Heilporn et al., 2021; Israel, 2015; Montgomery et al., 2015). Another advantage of blended MOOCs is that they reduce students' time on coursework. The reason for this is that blended MOOCs enable students to interact with their classmates and professors both online and in person, which can assist students in developing a stronger sense of connection to both the subject matter of the course and their fellow students. The University College of London (UCL) asserts that various tactics and strategies can help stimulate and maintain students' engagement with blended or hybrid learning (UCL, 2021). This assertion was verified by the findings of a study by Almutairi and White (Almutairi & White, 2018). Another advantage of blended MOOCs is that they can raise students' satisfaction level with their education (Brali & Divjak, 2016; Ho et al., 2022; Rajabalee & Santally, 2021). This claim is due to the increased number of possibilities for students to interact with their teachers and peers, which in turn can make students feel more supported and involved in the course they are taking. According to the findings of research conducted by Rajabalee and Santally (2021), there is a strong and favourable correlation between satisfaction and engagement levels. According to another study by Wu and Luo (2022), students showed positive views towards a blended course that included MOOCs. The researchers discovered that students expressed a higher degree of engagement, flexibility, a better knowledge of the learning content, and a more profound learning experience. However, Israel (2015) discovered that students' levels of satisfaction with the online component of blended MOOCs in classrooms were lower than expected. Finally, blended MOOCs have the potential to also lead to improved learning outcomes. After conducting a literature review on blended MOOCs (Bruff et al., 2013; Caulfield et al., 2013; Griffiths et al., 2014; Holotescu et al., 2014; Israel (2015) found that the majority of the studies claimed that blended MOOCs had a more positive impact on academic performance (as indicated by students' grades, test scores, and other standardised evaluations) in comparison to traditional classroom settings. Another study conducted by Wu and Luo (2022) discovered that students reported an increase in learner autonomy, motivation and engagement concerning blended learning as well as more interaction between educators and learners, favourable attitudes towards MOOCs as a superior learning method, encouraging comments, and relatively superior results from blended learning. The blended MOOC method helps learners get involved in different areas of expertise and other teaching and learning activities, improving teaching and learning materials (Cha & So, 2020). Finally, Brali'c and Divajak (2017) did a tracer study to examine how students changed over three school years and how blended instruction with MOOCs affected students. They found that students who did blended MOOCs wanted to take more MOOCs when they could choose which tasks to do online or offline. Also, they said that the blended MOOCs group did better than the others. The study also reported that most students who used blended MOOCs had outstanding learning experiences.

Similar benefits and advantages were observed for blended learning in the past. For example, Cha and So (2020) reported that blended learning could also improve the learning experience by making teaching and learning more flexible, supporting variety, and making things run more smoothly. Also, Cornelius (2019) used a blended learning approach finding that students were more interested in learning with others, reflecting and making connections, research and inquiry, staff-student partnerships, and skill development with the blended learning approach than with the offline campus approach. Furthermore, Cha and So (2020) reported that blended learning is better than traditional ways of teaching and learning because:

1. it lets students learn at their own pace;
2. it frees up class time for critical review and problem-solving;
3. it gives students more chances to learn "21st-century" skills that will be more useful when they look for jobs; and
4. it makes students feel like they own their learning.

Moreover, a structured review of 28 studies on the use of blended learning in higher education concluded that there is indirect evidence that the flipped approach leads to better academic performance and satisfies both students and teachers (O'Flaherty & Phillips, 2015).

It is imperative to recognise that in addition to these advantages, significant obstacles impede access and utilisation, especially in areas such as Ghana. Obtaining the required devices for participating in MOOCs is a significant obstacle. A considerable proportion of the population in some developing regions, such as Ghana, may lack access to personal computers or laptops (UNESCO, 2021a). The restricted availability of devices can be a substantial obstacle to effectively interacting with online course materials. Furthermore, the significant hindrance is in the expense and accessibility of data. To be able to use online courses, it is necessary to have a dependable internet connection and an adequate amount of data. In areas characterised by inadequate infrastructure and exorbitant data expenses, students may need help maintaining uninterrupted connectivity for the duration of their course (Twum, Mohammed & Pittman, 2024). The presence and dependability of internet connectivity infrastructure play a crucial role in determining the accessibility of MOOCs. Ghana's Rural areas sometimes need help with network coverage and stability (Siaw et al., 2020). The existence of this digital gap can lead to disparities in accessing online educational opportunities. Economic issues exacerbate the problem. Although MOOCs may have no or low fees, economically disadvantaged persons may face prohibitive indirect expenses related to device ownership and maintenance, data purchase, and ensuring a reliable internet connection (Hollands & Tirthali, 2014). Digital literacy is crucial, going beyond mere physical access. Some individuals who are interested in participating in MOOCs, particularly in areas with limited access to resources, may need to possess the requisite digital competencies to traverse online platforms proficiently (UNESCO, 2021a). This inadequacy can hinder their capacity to interact with the course material. The development and implementation of MOOCs must also consider the difficulties presented by the restricted availability of devices and data. Instructors and course developers must modify their teaching methods to cater to students with different access levels (Hollands & Tirthali, 2014). Tackling these obstacles is not solely about ensuring accessibility but also about promoting diversity and equity in education. To fully harness this technology's educational potential, it is imperative to ensure universal access to MOOCs, irrespective of socio-economic level or geographic location. Ultimately, although the advantages of MOOCs are considerable, it is crucial to acknowledge and tackle the notable obstacles associated with obtaining devices, data, and network infrastructure. These restrictions can disproportionately impact persons in developing regions such as Ghana, potentially restricting their ability to obtain high-quality education. It is crucial to make significant efforts to close these gaps and encourage inclusivity in online education to fully utilise MOOCs' potential as a tool for global learning.

1.2 Problem statement

Ghana's education system encounters a significant obstacle in university admission since only 20% of eligible candidates are accepted (TheGlobalEconomy.com, 2023; World Bank, 2023). Ensuring widespread availability of high-quality higher education is essential for personal advancement and the economic prosperity of a society. As traditional universities aim to grow, it is necessary to find creative solutions. Moreover, the educational environment is constantly changing, with technology playing a crucial role in influencing how students acquire knowledge and interact with instructional materials.

MOOCs are innovative educational technology developments that provide learning opportunities worldwide and require little or no payment. MOOCs are being recognised as effective instruments for increasing access to education, providing flexible options, and delivering high-quality learning experiences at a low cost (Fair et al., 2017; UNESCO, 2023). In places referred to as the global South and Sub-Saharan Africa (SSA), like Ghana, where it is crucial to increase university education availability for young students and individuals pursuing lifelong learning, MOOCs offer significant potential. Nevertheless, despite their many benefits, MOOCs also present difficulties and intricacies that require a thorough examination, particularly in the specified regions.

The incorporation of MOOCs into conventional university courses, referred to as blended MOOCs, presents a distinctive chance to combine sophisticated Western knowledge with traditional and regionally significant information, in line with the principle of "think globally but act locally"(Mohan, 2022). The research area of blended MOOCs is relatively unexplored, especially in the context of underdeveloped nations such as Ghana. The reason for this is that previous studies on blended MOOCs primarily concentrate on wealthy nations, disregarding the distinct requirements and obstacles faced in developing regions (Larionova et al., 2018). It is crucial to comprehend how students perceive and engage with blended MOOCs in this particular situation.

Although research has shown the potential advantages of blended MOOCs there are still significant gaps in our understanding of how they affect student engagement and academic performance, which are essential measures of educational success. Furthermore, there needs to be more research in Ghana on the efficacy of blended MOOCs in improving student engagement satisfaction and academic performance. The lack of research in this area prevents the effective use of blended MOOCs to increase access and enhance educational results in Ghanaian universities. Moreover, Fair et al. (2017) stress the necessity of conducting thorough investigations on blended MOOCs, highlighting multiple issues that require further examination. The study emphasises the different methods of incorporating MOOCs into conventional university modules and the various functions that MOOCs can serve within on-campus courses. Furthermore, it is crucial to examine the influence of differences in the percentage of MOOC learning materials used as module materials and the module timelines on student outcomes. In the Ghanaian setting, where educational needs frequently diverge from those in Western countries, examining the possibilities of blended MOOCs to align global knowledge with local demands is essential.

A significant obstacle in the MOOC setting is student engagement, as indicated by Almutairi (2018), who noted a need for more research on assessing students' engagement in the blended MOOC context. Engagement determines students' willingness to embrace and use instructional technologies. Active student engagement increases the likelihood of students embracing these technologies and deriving satisfaction from their learning experiences. Morrison (2014) supports this notion by emphasising that engagement is a robust indicator of performance in online courses.

The correlation between student engagement, satisfaction, and academic performance is widely recognised. Research has indicated that students who actively participate in their learning process generally have higher academic performance (Shin & Kang, 2015). Therefore, it is essential to comprehend the impact of blended MOOCs on these aspects. Moreover, studies have shown that blended learning and MOOCs have a beneficial impact on several learning outcomes, such as academic performance, student satisfaction, and skill enhancement (Freihat & Al Zamil, 2014; Griffiths et al., 2015; Najafi et al., 2014; Pérez-Sanagustín et al., 2016). Nevertheless, there has been a 1) lack of research on these learning outcome metrics on blended MOOCs in general and 2) lack of focus on the influence of the precise structure of blended MOOC courses on students' academic performance (Larionova et al., 2018).

Given the ongoing changes in education, it is crucial to investigate students' willingness to embrace blended MOOCs. Bryant (2017) emphasises the significance of comprehending students' perspectives on these technologies and key measures of critical learning such as engagement, satisfaction, and academic accomplishment. This research focuses on resolving the issue stated in this section about students' acceptance of Blended MOOCs, their engagement, satisfaction, and perceived academic performance. This study offers extensive insights into blended MOOCs' influence on students' satisfaction and academic performance. It is crucial to consider the possible future consequences of these findings, especially in regions such as Ghana, where the availability of high-quality education is an urgent issue. This study aims to improve educational methods and advocate for using blended MOOCs to connect global knowledge with local needs.

Previous studies have examined many facets of MOOCs. The current research, however, expands on the existing information by explicitly addressing a significant gap: the influence of blended MOOCs on students' views of learning and their perceived academic performances.

1.3 Purpose and Rationale of the Study

Stemming from the gaps identified in the preceding paragraphs, the study's main aim is to evaluate how students' use and engagement in blended MOOCs will affect their satisfaction and perceived academic performance. A combination of the revised community of inquiry (CoI), extended unified theory of acceptance and use of technology (UTAUT) and blended MOOC engagement models would be used to analyse students' usage acceptance and engagement with blended MOOCs.

To achieve the said goal, this study examines the influence of the four presences of the CoI model and seven factors of the UTAUT 2 models towards students' engagement in blended MOOCs leading to satisfaction and perceived academic performance. Thus, an amalgamated conceptual model comprising the community of inquiry and technology acceptance models would be developed and tested.

1.3.1 Research Objectives

Based on this main objective, the following specific objectives are derived:

1. Investigating the determinants influencing students' willingness to use blended MOOCs in the future.
2. Assessing the factors affecting students' actual use of the blended MOOCs.
3. Evaluating the four presences of the community of inquiry impacting students' engagement.
4. Exploring how students' engagement influences their satisfaction.
5. Exploring how students' engagement influences their perceived academic performance.
6. Examining how students' actual use of blended MOOCs influences their engagement.
7. Determining how the combined effect of actual use and engagement influence students' satisfaction
8. Determining how the combined effect of actual use and engagement influence perceived academic performance.

1.3.2 Research questions

The main research question is “how do students’ use and engagement with blended MOOCs influence their academic satisfaction and perceived academic performance”? In order to achieve the specific objectives above, these questions are derived:

1. How do UTAUT2 factors influence students' intention to use blended MOOCs?
2. What UTAU2factors affect students' actual use of the blended MOOCs?
3. What presence of the community of inquiry impacts students' engagement in blended MOOCs?
4. How does students' engagement with blended MOOCs influence their satisfaction?
5. How does students' engagement with blended MOOCs influence their perceived academic performance?
6. How does students' actual use of blended MOOCs influence their engagement with learning content?
7. How do students' actual use and engagement with blended MOOCs influence their satisfaction?

8. How do students' actual use and engagement with blended MOOCs influence their perceived academic performance?

1.3.3 Hypotheses

This section deals with the generic hypotheses. The detailed hypotheses numbered thirty will be dealt with in Chapter three during the description of the conceptual framework. The proposed generic hypotheses are as follows:

1. H1: UTAUT2 factors do not significantly influence students' intention to use blended MOOCs in the future.
2. H2:There is no significant relationship between factors affecting students' use of the blended MOOC system and their actual usage of the system.
3. H3: There is no significant relationship between the presences of the Community of Inquiry and students' engagement with blended MOOCs.
4. H4: There is no significant relationship exists between students' engagement with blended MOOCs and their satisfaction.
5. H5: There is no significant relationship exists between students' engagement with blended MOOCs and perception of academic performance.
6. H6: There is no significant relationship exists between students' actual use of blended MOOCs and their engagement with the system.
7. H7: There is no significant relationship exists between students' actual use and engagement with blended MOOCs and their satisfaction.
8. H8: There is no significant relationship exists between students' actual use and engagement with blended MOOCs and their perception of academic performance.

1.3.4 Rationale

This study explores the increasing popularity of MOOCs and their many formats acknowledging their ability to revolutionise higher education worldwide and diverse applications in increasing global access to education (Dalipi et al., 2018). Specifically, it centres on blended MOOCs, which provide a cost-efficient method of increasing educational opportunities in underdeveloped nations such as Ghana. Research on the adoption and usefulness of MOOCs in Sub-Saharan Africa, particularly in Ghana, is currently sparse despite their rich resources.

Furthermore, blended MOOCs are becoming increasingly popular in higher education because of their adaptability and ease of access. Nevertheless, it is crucial to comprehend the influence of these factors on student engagement, satisfaction, and perceived academic success (Commissiong, 2020; Rambe & Moeti, 2017). Furthermore, this study aims to determine the characteristics that impact students' acceptance and utilisation of blended MOOCs. This information may be used to enhance online course design and learning outcomes (Giasiranis & Sofos, 2020; Watson et al., 2016). Furthermore, although EdTech has demonstrated its ability to improve learning experiences, most studies on MOOCs mainly concentrate on specific metrics. This study aims to fill this void by investigating the levels of student engagement, satisfaction, and academic performance, as well as their acceptance of the underlying technology (Nortvig et al., 2018; Poon, 2012). This study offers a holistic knowledge of the online learning experience by integrating the revised community of inquiry (RCoI) and extended unified theory of acceptance and use of technology (UTAUT 2) models. The RCoI was proposed by Shea and Bidjerano (2010) to include "learning presence" or "learner presence" (LP) to the original CoI by Garrison et al. (1999). This aspect of integrating RCoI and UTAUT 2 must be included in the existing research agenda as it provides a holistic scope of students' online learning experience (Shih et al., 2013). Furthermore, the study investigates the effects of four presences– cognitive presence (CP), learner presence (LP), social presence (SP) and teaching presence (TP) – within the RCoI framework on student engagement in blended MOOCs. An awareness of these aspects can facilitate the development of efficient online learning environments (Garrison et al., 1999; Giasiranis & Sofos, 2020; Watson et al., 2016). Furthermore, there is a lack of substantial research to confirm the effectiveness of the revised CoI model in Sub-Saharan Africa. This study intends to address this knowledge gap (Wertz, 2022). Moreover, utilising the RCoI framework in MOOCs, particularly in the Ghanaian context, is relatively infrequent. This research enhances the comprehension of technology acceptance by incorporating students' engagement, satisfaction, and perceived academic performance into the UTAUT 2 model. This expansion contributes to a more comprehensive understanding of the topic (Venkatesh et al., 2016; Khechine & Lakhal, 2018). Finally, Commissiong (2020) opines that it is important to know how students feel about how they use technology, how they feel about their online learning experiences, how engaged they are, and how satisfied they are with their learning results.

This study investigates the acceptance and effectiveness of blended MOOCs in higher education in Ghana. It aims to offer valuable insights into the use of MOOCs in

Sub-Saharan Africa and contribute to the existing information on the subject. Additionally, it wants to guide policy-making and implementation of online education.

1.4 Significance of the Study

Universities worldwide, especially those in the developed world, are increasingly considering making MOOC and its variants an integral part of their curriculum (Dalipi et al., 2018). Producing a high-quality online course is expensive–thus, most universities in the global south cannot afford but making the product for free is an unthinkable venture for these universities. However, students from universities in the global south and their instructors must have experience using this technology to avoid being left behind. That is why blended MOOC, using MOOC as an OER, comes in handy, as both instructors and students can benefit from and gain the necessary exposure to this advanced teaching and learning tool free of charge. The result of the study will inform the university's management about their students' readiness to partake in an innovative online learning environment such as MOOC. The study at the macro level will lead to fulfilling the desire of the Government of Ghana to entice Ghanaians to use advanced EdTech in their daily activities of education, especially at the tertiary level (Ghana ICT4AD, 2003). The establishment of an open online university in Ghana since the result will predict whether Ghanaian students are ready to use online learning and MOOC as a substitute for bricks and mortar University. The findings will also raise awareness among educators, instructors, and facilitators regarding the significance of the online learning environment. This statement is because the results will ascertain the extent to which students are engaged, satisfied, and achieving academically. It will serve as a base for future policies and research in Ghana and elsewhere since minimal studies have been done with such objectives and approaches.

Because of the nature of openness, freeness, high-quality content from elite universities and taught by "superstar" professors and the possibility of bridging the digital and knowledge gap along with promoting lifelong learning, there have been copiously studies in the academic literature on MOOCs and its variants. For instance:

- Jordan (2015) grouped 257 scholarly articles published between 2009 and 2015.
- For their 2015 study, Sangrà et al. combed through 228 research articles from 2013 and 2014 published in scholarly publications.

- Veletsianos and Shepherdson (2016) analysed 183 empirical investigations between 2013 and 2015 to spot omissions in the existing literature. Zhu et al. (2018) also examined 197 studies published from 2014 to 2017.

Despite these colossal volumes of peer-reviewed papers published on MOOCs, relatively few authors and case-study areas were from Sub-Saharan Africa. In fact, Gasevic et al. (2014) indicated that 96% of the accepted proposals for grant applications submitted to the MOOC Research Initiative (MRI) originated from North America, Europe, and Asia, with none coming from Africa. Such a situation will result in a limited scope of understanding of MOOCs (Veletsianos & Shepherdson, 2016, p.202). To have an all-inclusive picture of the impact and widespread usage of MOOCs, research from other under- and non-represented regions, such as Africa, should emerge. Diversifying the perspective of MOOC research is the only way to make sense of the MOOC phenomenon. Thus, this study and its subsequent papers could bring Africans' views on MOOCs to bear, increasing the stock of academic papers on MOOCs from Ghana, in particular, and Africa, in general.

Moreover, the major themes to be covered in this study –students' engagement and academic performance, technology acceptance with UTUAT2 and promoting students' learning experience with CoI using blended MOOC–have received less attention globally, more so coming from a Ghanaian perspective. In this respect, this study's outcome will provide useful and insightful information on how MOOCs are being used in the form of open educational resources (OERs) setting to supplement classroom lessons in Ghana with different learning cultural settings from the providers of MOOCs.

Furthermore, the study’s results can be the basis for cross-cultural comparison between students from Ghana and those from other countries regarding their experiences in using blended MOOCs. Such a comparison is critical as MOOC has been considered the most important innovation in education in the last 200 years (Regalado, 2013) and is lacking in Ghanaian higher education institutions. The MOOCs for the study were initially traditional online courses from universities and institutions with specific target audiences before their conversion. Thus, awareness of worldwide students' variables (such as experience, attitudes and cultural backgrounds) would be useful in MOOCs' future design, making learning more effective and appealing.

1.5 Limitations and delimitation of the Study

Limitations and delimitations are essential factors to examine in every research study as they define the boundaries and constraints under which the research was conducted. Limitations are the study's shortcomings that arise from practical or theoretical restrictions and frequently pertain to the study's reliability and validity. Delimitations, in contrast, refer to the intentional decisions made by researchers on the extent and concentration of the study, which aim to restrict its boundaries.

This study acknowledges multiple limitations that arose along the research process:

1. Quantitative method: This study uses a quantitative approach for the study. However, it acknowledges the limitations of this methodology in capturing students' complex experiences and perceptions. Quantitative data is informative, but qualitative methods may yield more profound insights."
2. Sampling frame and cross-sectional data collection: - The study utilised a two-stage cluster sampling methodology, restricting the sample to those who exclusively had experience with blended MOOCs at the University of X (UCC). In addition, the study employed a cross-sectional strategy, gathering data within a defined period. The limitations could impact the applicability of the findings outside the specific population and time studied.

3. Specific e-learning platforms: The study examined a collaborative e-learning system that integrates MOOC and Moodle, managed and controlled by foreign organisations (Alison and Saylor) and UCC, Ghana. Students' opinions and experiences can differ while utilising various e-learning applications or completely distinct systems, such as WebCT, Blackboard, and Sakai.

Notwithstanding these limitations, the study used several strategies to mitigate their influence:

1. Addressing the constraints of sampling: The study aimed to achieve representativeness by selecting people with a diverse range of MOOC experience, even if the sample was collected from UCC, Ghana. Furthermore, advanced statistical approaches, such as stratified sampling, were utilised to improve the sample's representativeness.

2. Ensuring the reliability and validity of data: To improve the dependability and accuracy of the data, meticulous data gathering and analysis methods were adhered to. The questionnaire and survey were carefully developed, and the data collection procedures were strictly observed.
3. Focusing on generalisable factors: The study investigated key determinants impacting students' engagement, satisfaction, and perceived academic performance in blended MOOCs. Although the study focused solely on UCC in Ghana, the factors and models examined have broader relevance in diverse e-learning environments.
4. Ongoing Review and Adaptation: The ever-changing nature of technology and e-learning environments was recognised. In order to address this constraint, the research team committed to continuously examining and adjusting the study's conceptual framework and findings as the educational environment changes.

The parameters of this study were determined by its primary goals, research questions, and accessible resources, such as time and financial support. Notwithstanding these limitations, the study sought to offer significant insights into the implementation and results of blended MOOCs in the specific context of Ghana. The study's scope included:

1. Blended MOOCs, which use both MOODLE and MOOC platforms, yield insights that can be applied to diverse e-learning environments.
2. Examine the determinants that impact students' level of engagement, satisfaction, and perceived scholastic performance in the Ghanaian setting.
3. Prioritising examining students' experiences with blended MOOCs at UCC, Ghana, while acknowledging the possible applicability to comparable educational establishments.
4. The proposed conceptual framework focuses on the critical success factors for e-learning in a university context, which include technological acceptability, teaching quality, and support services.

Although these constraints establish the boundaries of this study, researchers are urged to modify and broaden the conclusions in various educational environments and situations. Although there are acknowledged constraints and boundaries, this study aims to provide significant knowledge to the education industry, namely in educational technology, electronic learning, online education and blended MOOCs. Subsequent research endeavours can expand on these discoveries and tackle certain contextual obstacles and possibilities.

1.6 Contributions of the study

Blended MOOCs may benefit from or suffer from the influence of unseen cultural factors on their usability and communication efficacy (Zahedi et al., 2006). Students in impoverished countries may be unable to participate in MOOCs because of cultural insensitivity, a lack of access to reliable internet, or a language barrier (Cheney, 2018). The effect of any technology–whether specific to educational or general use– differs in different societies due to culture and other settings. Furthermore, learning is also affected by culture, likewise learning with technology. Thus, researchers have to investigate all societies' views on accepting any technology to have worldwide usefulness. However, as far as the researcher is concerned, few studies have been conducted to investigate the Ghanaian dimension of blended MOOCs. After analysing 51 MA/MSc theses and PhD/EdD dissertations related to MOOCs published between 2008 and 2015, none of the theories, concepts, frameworks and models used was on UTAUT2 or COI model or both (Bozkurt et al., 2016). Again, an analytical study of the 265 research proposals received for the Major Research Instrumentation Program (MRI) grant arrived at the same conclusion (Gasevic et al., 2014, pp.146-147). In this respect, the study is a novelty as it has not been previously considered. Furthermore, blended MOOC is becoming popular, but a study of this magnitude has yet to be conducted, using UTAUT2 and CoI to determine its future re-use by students. Thus, this study's strength lies in filling the knowledge gap in the discipline of blended MOOC in general. The research will fundamentally contribute to the body of literature on blended learning with MOOC as an open educational resource in general and specifically within Ghana and sub-Sahara African context. From both theoretical and practical perspectives, the research will make contributions to knowledge as follows:

- It provides a primer on the literature around blended MOOCs, technology acceptance models and theories, and the community of inquiry looking into how to increase students' openness to and use of educational technology.

- From the Ghanaian point of view, it affirms and supports the blended MOOC engagement model and the UTAUT extensions around the MOOC context. This study is one of the few that has developed and empirically tested such an integrated theoretical framework to the best of the researcher's knowledge. As a result, this research provides a more nuanced comprehension of how the characteristics of students influence the usability and interactivity of blended MOOCs from the vantage point of Ghana and sub-Saharan Africa.
- This study is one of the very few that combine two models with different end goals together– online learning experience and technology acceptance–via another model blended MOOC engagement model. The technology acceptance model is a generic model for all technology irrespective of where it is being used; on the other hand, the community of inquiry is developed to enhance the online learning experience at a much lower level. Finally, from this research's perspective, the blended MOOC engagement model was explicitly designed for the blended MOOC environment at the very lowest level. The research is to find out how a narrower model like CoI relates with a very narrowest model like blended MOOC students' engagement and which in turn relates with a much generic model like UTUAT extension, all leading to the influence to accept and re-use the latter. This research will determine whether or not the acceptance of a technology (blended MOOC) is influenced by the underlying technological factors alone or indirectly affected by perceived online learning experience, engagement, or individual personal characteristics. To the researcher's knowledge, no other research has measured such details within the Ghana and sub-Saharan Africa settings.
- It gives a general picture of the current utilisation of MOOCs in Ghanaian universities. The discoveries will aid Ghanaian universities' readiness to use online learning or MOOC to expand access to their programmes for regular students or lifelong learners without necessarily physically coming to campus.
- The proposed conceptual framework for the research consists of three models– CoI, students' engagement model for blended MOOC and UTUAT but there exists no study that combines these three models together. Apart from the novelty of the conceptual framework, the same can be said of the following separate parts of it:

- Most studies on CoI deal with the original three presences of social, teaching and cognitive; however, this research is one of the very few that validate the four presences that include learning presence as proposed by Shea and Bidjerano (2010).
- Venkatesh et al. (2016) asserted that there are four types of UTAUT Extensions. Most studies on UTAUT end with technology use with or without a new moderation mechanism. At the same time, few studies include either a new exogenous mechanism, a new outcome mechanism, or both. However, this study utilises a new exogenous mechanism (educational task value) and a new outcome mechanism (students' engagement).
- Ever since Almutairi (2018) proposed the student engagement model for blended MOOC, no research has validated the model either wholly or partly. Thus, this research is the first to validate an abridged version of the model.

1.7 Student learning and student engagement for online education

In e-learning, both "students' engagement" and "students' learning" are essential and linked ideas. Nevertheless, student engagement is more often used and preferred than students' learning in e-learning settings like online learning, blended learning, MOOC and blended MOOC (University College London., 2021). This claim is because student engagement has a broader scope and puts more stress on active participation in the learning process. "Students' engagement" means that learners are actively involved, take part, and care about their learning (Fredricks et al., 2004). It is a complicated idea that can be affected by many things, such as the level of teaching, the student's background knowledge, and the student's motivation. On the other hand, Biggs and Tang (2011) define "students' learning" as the process of acquiring, integrating and using information, skills, abilities and competencies. (Bransford et al., 2000). It refers to the mental processes used to gain and build new information, understand concepts, and learn new skills. Learning means getting smarter, thinking critically, and knowing more about a specific topic. It is a more objective measure than student engagement, and there are many ways to test it, such as in examinations, quizzes and projects. Even though teaching is supposed to help students learn, they need to be involved for that to happen. When students are interested in what they are learning, they are likelier to want to learn and remember what they have learned. There is a strong link between how engaged students are and how much they learn. Studies have shown that students are more likely to learn well when they are interested in what they are doing. Nevertheless, it is important to remember that student learning is affected by more than just how engaged they are. Other things also play a role, like the quality of the teaching and what the student already knows.

Hollister et al.'s (2022) study shows how significant engagement is for attending class and learning. About 72% said not paying attention during lectures hurt their online learning experience. The result made it hard for them to stay in touch with their classmates and teachers and slowed down their pace of homework. Also, Stephenson et al. (2020) suggested that more engaged students have a better chance of meeting learning goals, as shown by their higher course satisfaction and performance. In the end, they said that high achievers are engaged learners. Moreover, Coates (2005, as cited by Almutairi, 2018) stated that student engagement is a dependable indicator of student learning, as it closely approximates the essential and comprehensive information about students' learning outcomes. Finally, Commission's (2020) study online learning showed that engagement, satisfaction and students' use of self-regulatory tactics in the classroom was significantly correlated with their grades and persistence in challenging courses. The study shows that student engagement is crucial for getting good learning results in online learning settings. Thus, in this study, students' engagement will be used instead of students' learning though the title deals with the latter.

1.8 Definition of key concepts

Most of the technology-driven terminologies do not have universal definitions. This may be due to the young age of the discipline in comparison with the likes of Mathematics, Science, Philosophy, *etc*. and also due to the rapid rate at which the concepts are modified. In this respect, explanations of the frequently used or key terms used in this study are given in this section.

1. Blended Learning: It is the combination of online and face-to-face instructional delivery modes into one new whole that complements the strengths and weaknesses of each other. Here, face-to-face and online technologies, activities, principles and media are combined to create a new synergy.

2. Blended MOOCs: This is a combination of campus-based courses with MOOC content. There are a variety of models (implementation strategies) that the blend takes to achieve the learning objective of the course. The role played by the MOOC is not fixed but is determined by the model, which can be either as the primary source of course content and learning activities or as supplementing and enhancing the face-to-face instruction facilitated by an instructor who deploys additional learning activities and assessments.
3. Community of inquiry (CoI): It pertains to the nature of knowledge generation and scientific inquiry (Garrison et al.,2000). It is generally characterised as a collective of individuals examining difficult circumstances through empirical or conceptual investigation (Garrison et al.,2000). It highlights the idea that knowledge is inherently connected to a social framework and, as a result, necessitates mutual agreement among participants in the inquiry process to be considered valid (Garrison et al.,2000). CoI originally constituted three elements essential to an educational transaction - cognitive presence, social presence, and teaching presence. However, Shea et al. (2010) suggested including the learning presence, calling it the revised Community of Inquiry model used for this study.
4. EdTech: This is also known as EduTech and is a short form of Education technology. It is a digital technology designed and deployed for education use to enhance and supplement teaching, learning, assessment, administration and other educational processes.
5. E-learning: This is learning mediated by digital technologies to access the educational curriculum and participate in educational activities outside the physical classroom settings. Many technologies exist, including radio, television, and disc, but the Internet is the preferred choice due to its availability, economics, interactivity and multimodality.
6. Global South: This refers to countries with lower economic and political development levels than the Global North ("Global North and Global South, "2024). The Global South is a geopolitical concept that categorises countries based on their distinctive socio-economic and political qualities ("Global North and Global South, "2024). The United Nations Conference on Trade and Development (UNCTAD) defines the Global South as encompassing Africa, Latin America and the Caribbean, Asia (except Israel, Japan, and South Korea),

and Oceania (excluding Australia and New Zealand) ("Global North and Global South, "2024). Most countries in the Global South are often characterised by a low standard of life, lower wages, high poverty rates, dense populations, limited educational possibilities, and inadequate health systems, among other challenges ("Global North and Global South, "2024).

7. Instructional Delivery: This is the collection of interactive skills the teacher exhibits to facilitate or promote learning in a teaching and learning setting, either face-to-face or online. From it, students are given opportunities to build on their previous knowledge, skills or experiences that would enable them to solve problems or create worth. It is based on the teacher's personal approach to teaching, guided institutional expectations and student demand for quality instruction. Some skills the teacher should acquire for effective instructional delivery are a) time management, b) technological literacy, c) assessing and evaluating, d) presenting content, e) motivating students, f) generating enthusiasm, g) communicating effectively and h) questioning.
8. Learning Environment (LE): LEs encompasses the spaces students' study in traditional classrooms or online platforms. According to Bates (2015), learning environment includes factors such as the students' characteristics, the instruction's objectives, the methods most likely to foster learning, the methods most likely to measure and motivate improvement, and the culture permeating the classroom.
9. Learning presence (LP): Shea and Bidjerano (2010) defined that learning presence involves learners' proactive and self-regulatory engagement in online and mixed learning settings. It requires critical thinking, self-efficacy, and self-regulation to generate meaning. Learning presence lets students control their learning in online and blended learning contexts, such as self-efficacy, self-regulation, and other cognitive, behavioural, and motivational aspects (Honig & Salmon,2021) to extend the CoI framework, encompassing cognitive, social, and teaching presence.
10. Online learning: This is a course where most or all of the content is delivered online using the Internet with no physical interaction. (Allen, & Seaman, 2007).
11. Mobile computing: It encompasses the utilisation of portable computing devices, such as smartphones, tablets, and laptops that are easily transportable by users.

These devices have been developed to possess a low weight, small size, and effortless usability when in motion.

12. Mobile learning: It is a specialised form of internet-based electronic learning that utilises mobile computing devices to provide instructional content to students. Mobile learning is a widely accessible and portable method of education that enables students to learn at any time and in any location, utilising their mobile devices.
13. MOOC: It is a model allowing educational materials to be available online to unlimited students (Educause Learning Initiative, 2011).
14. Sub-Saharan Africa: This is the geographical region of Africa located south of the Sahara Desert. It consists of forty-nine countries (including Ghana, the subject of the study) and a population of 1.1 billion people who reside in this place and share common socioeconomic characteristics (Kuhlman, 2022), thus usually separated from North Africa, as shown in Figure 1.1. Geographically and culturally, the remainder of North Africa differs from Sub-Saharan Africa (Kuhlman, 2022). The African Transition Zone acts as a dividing line between North African, predominantly Islamic, and Sub-Saharan Africa, which animist and Christian beliefs characterise (Kuhlman, 2022). North Africa encompasses seven nations with a population of 240 million people (Kuhlman, 2022).
15. Unified Theory of Acceptance and Use of Technology (UTAUT). This technology acceptance model is designed to explain user intents to utilise an information system and the resulting usage behaviour (Venkatesh et al., 2003). According to the theory, there are four fundamental concepts. The four factors that impact user behaviour are 1) performance expectancy, 2) effort expectancy, 3) social influence, and 4) facilitating conditions. The initial three factors directly influence the intention and behaviour of usage, whereas the fourth factor directly influences the user's behaviour (Venkatesh et al., 2003). The impact of the four fundamental constructs on usage intention and behaviour is believed to be influenced by gender, age, experience, and voluntariness of use(Venkatesh et al., 2003). The UTAUT model was created by analysing and combining the components of eight previously used models that aimed to explain the behaviour of individuals when using information systems (Venkatesh et al., 2003).

16. Web-enhanced instruction is a technique of teaching in which the Internet is used to supplement traditional classroom teaching by enabling online communication, collaboration, and document sharing and storage (Angulo & Bruce, 1999).

1.9 Structure of dissertation

This chapter gives a synopsis of the significant sections of the dissertation and the methods used to accomplish the stated goals.

Chapter 1—Background and Context This chapter provides background on e-learning adoption to improve university access, particularly in the global south. Problem statement, research objectives, questions, definitions, and limits are covered. It closes with a dissertation structure and organisation summary.

Chapter 2—MOOC/Blended MOOCs This chapter introduces MOOCs and their evolution from e-learning to blended learning. UCC's e-learning history and mixed MOOC logic will be discussed. The merits and cons of mixed MOOCs at UCC, including blended learning approaches, will be discussed.

Chapter 3—Technology Acceptance and Adoption Models The chapter will address technology acceptance and use theories and models in detail. It will defend UTAUT 2's inclusion in the conceptual framework and review MOOC technology adoption literature.

Chapter 4—Online Learning Frameworks Online education frameworks like community of inquiry, connectivism, and online collaborative learning will be examined. The chapter will explain why this study used the Community of Inquiry (CoI) paradigm and analyse its use in blended MOOCs.

Chapter 5—Proposed Conceptual Framework This chapter presents a framework incorporating CoI, UTAUT 2, and blended MOOC engagement methods. It will support model changes and propose research hypotheses, defining each concept.

Chapter 6—Research Methodology The chapter will explain the research philosophy, approach, design, and sample method. The data collection instruments, justification, analysis, and statistical methodologies will be covered. Ethics will also be considered.

Chapter 7— Data Analysis and Results Discussion. It will analyse survey replies, display descriptive statistics, and check normalcy. KMO and Bartlett sphericity tests will be covered in the chapter.

Chapter 8— Measurement Scale Analysis Partial Least Squares Structural Equation Modelling (PLS-SEM) will analyse the measurement model's validity and reliability.

Chapter 9— Structural Model Results and Discussion This chapter will examine PLS-SEM structural model results, including hypothesis testing and importance-performance MAP Analysis.

Chapter 10—Summary, conclusions, and recommendations. The final chapter will summarise and relate the study's findings to the research goals. It will draw conclusions, suggest future research, and emphasise the study's contributions to student engagement, satisfaction, and performance in blended MOOCs.

Chapter 2 will examine MOOCs and their significance to the research.

CHAPTER 2: MOOCS, ENGAGEMENT AND LEARNING OUTCOMES

2.1 Introduction

Section 2.1 introduces the chapter, providing a foundation for examining MOOCs and their impact on student participation and learning outcomes. The following sections explore electronic and blended learning (2.2 and 2.3), offering fundamental insights into contemporary educational paradigms. The conversation encompasses the analysis of MOOCs from a pedagogical standpoint, explicitly focusing on learner-centeredness, curricular structure, and assessment methodologies in sections 2.5 and 2.6. Sections 2.7 and 2.8 delve into MOOC delivery's technological and pedagogical components. The chapter also discusses the necessity of researching blended MOOCs (2.9) and their influence on learning (2.10). Sections 2.11 and 2.12 extensively explore the topic of student engagement in general and specifically in MOOCs. Section 2.13 deals with learning outcomes regarding students' satisfaction and academic performance..

The capacity of MOOCs to simultaneously give the same experience to tens of thousands of students breaks the pattern of conventional university education, indicating their potential to expand access to education and decrease educational costs (Groves, 2012). Increasing access has been the goal of all universities and any EdTech solution that “rides on the wings” of the internet or web can attain global reach. Again, with the increasing cost of 'bricks and mortar education and the 'swallowing effect' of students' debt, any mode of schooling that combines high-quality instructional delivery at the barest minimum cost has the potential to be embraced by education seekers. That is why MOOCs should occupy the attention of all learners, educators, teachers, administrators and policymakers. For any discussion on MOOCs, it is prudent to start with electronic learning and, then dove-tail to blended learning, where blended MOOC, the topic of this research, takes its root.

2.2 Electronic learning

Electronic learning, also known as e-learning or eLearning, is a network-enabled transfer of skills, information and knowledge. It is delivered synchronously or asynchronously to many users, with enhanced knowledge, understanding and skills as the destination. There are many different types of e-learning, including but not limited to the following: Computer-assisted learning via a network, the Internet- and the web is characterised by distributed; thus, it is virtual and remote learning. E-learning instruction is delivered synchronously or asynchronously to many users, with enhanced knowledge, understanding and skills as the destination. The rubric for this e-learning continuum is shown in Figure 2-1.

Proportion of Content Delivered Online	Type of Course	Typical Description
0%	Traditional	Course with no online technology used — content is delivered in writing or orally.
1 to 29%	Web Facilitated	Course which uses web-based technology to facilitate what is essentially a face-to-face course. Uses a course management system (CMS) or web pages to post the syllabus and assignments, for example.
30 to 79%	Blended/Hybrid	Course that blends online and face-to-face delivery. Substantial proportion of the content is delivered online, typically uses online discussions, and typically has some face-to-face meetings.
80+%	Online	A course where most or all of the content is delivered online. Typically have no face-to-face meetings.

Figure 2-1.The Sloan Consortium's e-learning continuum.

*Source***.** Allen, Seaman & Garrett (2007).

- Traditional **face-to-face(F2F)**: No e-learning platform is involved in this case though the facilitator could use graphical presentation software such as PowerPoint.
- **Web enhancement**: In this case, an e-learning platform is used to host course contents (syllabus, PowerPoints, recommended book in pdf) and course-level announcements. The web supports lecturers as well as students after class exercises.
- **Blended learning**: There is a conscious mix of the classroom's activities for blended learning into face-to-face and online. Although classroom time decreases, it is not abolished since some tasks are conducted in person while others are completed online. Blended learning can involve anything from fewer in-person classes per week and more online sessions to traditional on-campus sessions for sandwich or summer periods preceded or subsequently followed by online study. It might involve laboratory or practical on-site sessions on weekends or nights, with the remainder completed online. Some believe blended learning should be

restricted for all courses, with x% online ranging between 0 and 100 (i.e., 0<x<100).

- **Fully online**: The face-to-face classroom is replaced entirely with a virtual space in this form. An online course provides education exclusively over the Internet. The e-learning platform is the primary interface between the facilitator and learners. With this form, everything done face-to-face is done online, except the assessment at the end of the semester. The summative assessment may need to occur in one of the authorised physical sites chosen by the teacher or the institution. Some institutions questioned the viability of online assessments due to concerns about student cheating, impersonation, system failures, and internet disruptions (Allen et al., 2007). However, the COVID-19 pandemic has advanced e-learning technologies and assessment methods. Many of these difficulties have been solved by innovative methods, including improved proctoring, learning management systems, and internet access (Almossa & Alzahrani,2022). However, online assessment efficacy and fairness debates persist, stressing the necessity for continual study and adaptation to changing educational demands and technical capabilities (Yazdi & Hatami, 2023).

By observation, what differentiates these strategies is the amount of time spent in a classroom versus online digital technologies for instructional delivery. This amount is labelled as the percentage of content delivered online. This section takes the place of the standard classroom lectures and other activities requiring seated participation that the teacher conducts. Other possible activities that could be used for the replacement/supplement/complement are 1) collaborative learning via wiki; 2) interactive activities such as online quizzes, usually multiple-choice questions; 3) virtual team projects; 4) synchronous chat sessions and 5) asynchronous discussion forums. Though most works of literature use blended learning and hybrid learning interchangeably, others believe there is a subtle difference between the two. The difference highlighted by the latter group looks like this: "with blended, no online instruction time is substituted for F2F time, while with hybrid, the time traditionally spent in the classroom is reduced but not eliminated" (Driesen, 2016; Panopto Inc., 2019; Siegelman, 2021; Steele, 2020). The implication is that online activities do not replace F2F activities with blended learning but complement them, serving as add-ons. With hybrid on the one hand, online activities do replace F2F activities. Steele (2020) considers blended learning a course for identical learners with activities grouped into classroom and online.

On the other hand, with hybrid learning, the course has some learners participating in-person in the classroom and others accomplishing so virtually online. In both cases, there are the same facilitator(s) and course with two groups of learners for hybrid and one for blended. Concerning the various instructional delivery modes, the US Department of Education made the following observations (Means et al., 2013):

- Students who learned the same content via conventional face-to-face sessions performed marginally worse than those who learned the same content through online instruction.
- Those who participated in only online classes fared better than those who participated in face-to-face courses.
- In contrast, students who participated in hybrid courses scored better than fully online students.
- Instructional activities from blended learning activities are more significant advantages than those from face-to-face.

From this, blended learning as an instructional delivery strategy stands out among its other F2F and online learning counterparts.

2.3 Blended learning

EdTech is used worldwide to complement or supplement traditional face-to-face classroom teaching through blended, hybrid or mixed-mode instructional delivery or learning strategies. Johnson et al. (2016) recognised blended learning as one of the major trends and most critical developments in the current educational landscape. Most educational institutions are either unaware or not utilising blended learning to its fullest potential. Blended learning has no universally accepted definition, but the most widely used perspective comes from combining brick-and-mortar classroom settings versus online. The allotted instructional period is shared between the two modes in a portion determined by the lesson objective and activities. Blended learning is a form of teaching that combines the traditional face-to-face (F2F) classroom mode of teaching with the online learning (OL) mode of teaching. It uses a mixture of pedagogical paradigms such as behaviourism, cognitivism, connectivism and constructivism, to generate a high-quality learning experience. The ultimate goal for learning, especially at the university level, is to fully integrate the F2F and OL components into a single whole that meets the course's learning objectives. Higher education has embraced and implemented blended learning for a variety of reasons, such as the need for more flexible and personalised curricula, the need to accommodate students' diversity through differentiated instruction and the desire to increase students' interest in and participation in their course materials.

2.4 E-learning at the University of Cape Coast

The University of Cape Coast (UCC) first used the learning management system (LMS) in 2002. At that time, the University was a Learning Centre for the Bachelor of Computer Science programme for the African Virtual University (AVU) in Kenya. Content for the programme came from the Royal Melbourne Institute of Technology, Australia, via the WebCT LMS. After the programme's termination, the Computer Centre (now Network and Infrastructure Services) at UCC has hosted a MOODLE LMS since 2007 with low participation. In 2012, a workshop series was organised to encourage lecturers to use the platform to enhance the F2F courses. Participants were confronted with the following:

- The issue of increased workload in teaching online, as discussed above,
- Lack of skill to create compelling online courses in UCC,
- Lack of budget to outsource content creation.

Creating one hour of e-learning costs about $10,000, according to Chapman Alliance (2010) data. The more interaction and media richness there is, the more time and money it takes to implement. For an hour of ready online learning material to be produced, Raccoon Gang (2018) found that it needs 100-160 hours of effort, costing $8,880-$28,640 ($18,760) on average. The study further stated that the costs could be lowered by up to 30 per cent if skilled contractors do the job. Upon the enormity of teaching online, designing and creating content and facilitating classes, stakeholders should readily seek available learning objects in the form of adaptable open education resources (OER). Again, merely converting face-to-face lessons to online versions does not make pedagogical sense, according to Guàrdia et al. (2013). As the facilitator of the said workshops, this researcher started searching for online OERs for courses taught at the University X. The first point of call was the Massachusetts Institute of Technology's

OpenCourseWare, a static-based material made up of PowerPoint and portable document format (pdf). SWAYAM (Study Webs of Active Learning for Young Aspiring Minds) is the Massive Open Online Course (MOOC) platform created by the Indian government's National Programme on Technology Enhanced Learning (NPTEL) is a part, was surveyed. At that time, the content of NPTEL contained video lectures without transcription, discussion forums and quizzes. In 2014, this researcher asked his postgraduate students for his Database course to participate in a moderated Database Design course on Coursera facilitated by a Stanford Professor, Jennifer Wisdom. The success of the Coursera experience caused other lecturers to request their students to enrol in MOOCs that teach content similar to their on-campus subjects at UCC. Since then, students at the university have registered for many MOOC platforms some of which are shown in Table 2-1.

Table 2-1:Sample of blended MOOCs and platforms used in UCC.

Platforms	**Courses enrolled**	**Corresponding UCC courses**
	Microsoft Office 2010	ITS101: Information technology Skills (from 2016-2018)
	Microsoft Office 2010-Revised in 2018	ITS101: Information technology Skills (from 2018- 2020)
		APM804S: Computer Applications in Project Management (from 2017- 2019)
	Microsoft Digital Literacy - IT Basics, Internet & Productivity Programs,	EPS712P: Computer Applications in Education (from 2016- 2020)
		EPS713P: Computer Basics (2018)
Alison		AGN106A- Introduction to ICT (from 2016- 2020)
	Alison ABC IT - Computer Training Suite	ITS101: Information technology Skills (from 2016-2018)

		AGP 101: Introduction to computers
	Microsoft SharePoint 2010	APM804S: Computer Applications in Project Management (from 2017- 2019)
	Diploma in Project Management	APM804S: Computer Applications in Project Management (from 2017- 2019
	Microsoft Access 2013 for Beginners - Start Your Database Journey Microsoft Access 2013 - Advanced. Master Databases	CSC216: Database Design (from 2019- 2020) INF215: Database Systems I (from 2019- 2020) CSC403: Database Design (from 2014- 2018) EIT806: Database Implementation (from 2015- 2019)
	Introduction to E-learning Theory and Practice - Revised	EPS712P: Computer Applications in Education (from 2018- 2020)
	Java Programming for Complete Beginners	EIT816: Programming Language II (from 2019- to date)
	Scratch - Teach Computer Programming in Schools	EIT816: Programming Language II (from 2018- 2020)
	Microsoft Word 2010- Revised in 2017 Microsoft Excel 2010- Revised in 2017 Microsoft PowerPoint 2010- Revised in 2018	ITS101: Information technology Skills (from 2021)
Coursera	Introduction to Database Systems	EIT806: Database Systems (2014-2015)

Edx	Management Information Systems Survival Guide	BUS304: Management Information Systems II (2014-2018) EMG303: Management Information Systems II (2014-2018) MGT208: Management Information Systems II (2016)
	Database Essentials	CSC403: Database Design (2016-2018)
Saylor	BUS206: Management Information Systems	BUS303: Management Information Systems II (2015- to date) EMG304: Management Information Systems II (2015- to date) MGT810S: Management Information Systems (2016-2018)
	BUS303: Strategic Information Technology	BUS303: Management Information Systems II (2015-2017) EMG304: Management Information Systems II (2015-2017)
	CS305: Web Development,	EIT816: Programming Language II(2016- 2017)
	CS403: Database Design	ADM408: Introduction to Database Concepts (2015- 2016) CSC403: Database Design (from 2016- 2018)

2.5 MOOCS

MOOCs are online courses that are free and open to interested participants (usually in hundreds of thousands) to partake in simultaneously. They provide a free full educational experience online, regardless of their prior entry qualification, training or education. MOOCs are popular across the globe due to their free, high-quality material, large enrolment and other appealing aspects. In 2008, when describing an online course taught by Stephen Downs and George Siemens to around 2,000 students, Dave Cormier, from the University of Prince Edward Island in Charlottetown, Canada, and Bryan Alexander, from the National Institute for Technology in Liberal Education in Georgetown, Texas, are credited with creating the term massive open online course (MOOC). Thus, the first MOOC was "Connectivism and Connective Knowledge," created and delivered by Stephen Downes and George Siemens in 2008(Liyanagunawardena et al.,2013). MOOCs gained popularity not only in the developed world but also in the business world. Sebastian Thrum and Peter Norvig, two Stanford professors, launched a new course in artificial intelligence in 2011 called CS221. with 160,000 enrolled students. In 2012, Laura Pappano wrote an article in Time magazine with the caption "The Year of the MOOC". MOOCs have become popular with major companies (such as Udacity, Coursera and edX) and their platforms.

They provide individuals with a glimpse of the interesting, intriguing and innovative courses and topics taught at top institutions worldwide while guided by experts in their fields. MOOC platforms have made quality education accessible to everyone, irrespective of the learner's status or location, but a fee is charged for those interested in certificates on completion. MOOCs are online learning spaces that bring together hundreds of thousands of participants globally in an online space. They provide opportunities for students from developing countries to taste high-quality education at practically no cost and act as a "potential equaliser" in access to knowledge. MOOCs also reduce the digital divide, particularly for those from the global South, by addressing all three layers of the divide: accessibility, usability and empowerment.

For people in the developing world, these platforms provide avenues for learning academically and professionally, thereby bridging the knowledge divide between global

North and South in all issues leading to economic development, a better quality of life, innovation and proper management of resources. The importance of MOOCs cannot be overemphasised as they can change the traditional education system that has been around for ages and provide an authentic avenue for lifelong learning and continuous professional development. Plasencia and Navas (2014) suggest the following characteristics of a MOOC:

- Should be a course with exams to measure knowledge learning.
- Be worldwide and massive, with no geographical constraints for pupils.
- May be taught online using traditional course materials such as videos, lectures, problem-solving publications and user-interactive forums to develop a community of students, instructors and teacher assistants (TAs), who interact together to achieve the course objectives.

MOOCs are a form of blended learning that combines formal and informal learning in a complementary format. They attract participants from diverse backgrounds and countries, but the available demographical data indicate that most MOOC participants are from developed nations, with meagre participation from others, especially from Africa. There are tonnes of rich academic materials and knowledge in MOOCs, but the limited engagement of the developing world comes from developing country users in the west. Learners' confidence, prior experience in learning in a MOOC and motivation were essential determinants of engagement in a MOOC. Challenges to using MOOCs in developing countries include access to digital infrastructure facilities and technologies, poor digital literacy skills, language barriers, cultural sensitivity, multiple learning spaces and information overload.

MOOCs have the great potential to change the academic landscape of countries in the developing world, but learners' circumstances and context should be considered for it to come to fruition. Generally, MOOCs are classified into two major groups: xMOOC (mechanical or eXtended MOOC or massification MOOCs) and cMOOC (connectivist or connective) MOOC. xMOOCs mimic the traditional university online course format centred on a single expert–the professor– (or lecturer) transferring their knowledge to as many students as possible (some reaching 160,000). xMOOCs and cMOOCs are two different approaches to learning. xMOOCs primarily emphasise the dissemination of knowledge through video presentations, brief quizzes, and assessments, while cMOOCs focus on co-creating knowledge, creativity, autonomy and social networking learning.

Massification MOOCs are essentially objectivists and behaviourists regarding their learning approach, while cMOOCs take the connectivist approach to learning. Features of xMOOCs include pre-planned platform software, video lectures, computer-marked assignments, peer evaluation, supplementary materials, a centralised comment/discussion section with minimal or no moderation, badges or certificates, and data analytics on student performance. The characteristics and features of social media, participant-generated content, decentralised instruction, and the absence of centralised examination are the hallmarks of cMOOCs. Altinpulluk and Kesim (2016) have identified 20 new variants of MOOC. The emergence of MOOC variants has led to a reduction in favour of MOOCs and the loss of their popularity.

These variants are designed to provide innovation that can easily be adapted to meet the needs of a segment of the population such as low-cost leadership, product differentiation, specialising in a certain market and fostering close relationships with customers and suppliers. MOOCs are both technological and pedagogical tools for disseminating knowledge to large numbers of students at a low cost and when all three points of view come together properly within a course, the resulting synergy effect is the attainment of the course's goal. MOOCs have created environments that support scholarly communication and serve as vehicles for an organisation to attain a competitive advantage and provide individual satisfaction. MOOC is a sociotechnical system that needs a proper balance between pedagogy and technology to achieve the educational goal of the course. It is essential to realise that technology supports student learning and not student learning supporting technology.

The academic success rate of MOOCs is an issue of considerable interest and debate within the educational community (Jordan, 2015). However, it is essential to acknowledge the limitations and complexities associated with measuring the academic success rate of MOOCs. While enrolment numbers may be substantial, completion rates tend to be much lower, raising questions about the efficacy of MOOCs in facilitating sustained learning and performance (Kumar, 2022; Liyanagunawardena et al.,2013). For instance, Poncho (2015, as cited in Maphosa & Maphosa,2023) observed that African learners have a 5% MOOC completion rate. Factors such as learner motivation, prior experience, and external commitments can significantly impact engagement and retention in MOOCs (Garcia et al. (2023). Additionally, the lack of formal accreditation for completing MOOCs may deter some individuals from fully committing to these courses

(Pundak et al., 2014). Moreover, MOOC participants' diverse demographics pose challenges in uniformly assessing academic success (DeBoer et al., 2013). Participation rates from developing countries, particularly in Africa, remain relatively low compared to those from developed nations (Mutisya & Thiong'o, 2021). Other researchers highlight issues of access to digital infrastructure, language barriers, and digital literacy skills, which can hinder meaningful engagement with MOOC content, especially learners from the global south and sub-Saharan Africa Mutisya & Thiong'o, 2021.

Pedagogy should dictate teaching with technology, thereby enhancing learning effectiveness and efficiency. Technology sets the tempo and creates the music while pedagogy determines the moves to take. MOOC as an educational technology will be more effective when paired with an appropriate teaching strategy promoting learning. This mutualistic association prompts Anderson and Dron (2011) to use the dancing metaphor to describe pedagogy and technology in co-dependent relationships.

2.6 MOOCs from a pedagogical viewpoint

MOOCs are online learning environments that provide mainly asynchronous, collaborative and distance learning opportunities. Instructional delivery is how instructors approach teaching based on their own professional identity to help create a unique classroom culture. Pedagogy refers to the activities of educating, teaching or instructing that Instructors go through to deliver the lesson outcomes. Educationists have classified academic fields into four categories: hard pure (e.g. natural sciences), soft pure (e.g. humanities), hard applied (e.g. engineering) and soft applied (e.g. education). These fields assist in shaping the categorisation of MOOC design (Neumann, 2003; Neuheiser, 2002). The pedagogies of MOOCs are still garnering much interest, especially in higher education institutions because of how teaching and learning are done. MOOC pedagogy's success is difficult to prove empirically. Aside from the massive number of participants, these pedagogical approaches of MOOC are primarily that of online learning. The pedagogical characteristics of MOOCs shall be discussed in the following paragraphs.

2.6.1 Learner-centredness

The pedagogy that underpins MOOC is placing the learner at the centre of the educational process so that the learner can make decisions regarding their learning. Researchers (Grünewald et al., 2013; Sanna & Anne-Maria, 2015) reveal that in this pedagogy, the learners decide what to learn, when to learn, where to learn, how to learn and to what extent they commit themselves to the learning community. These make the learner an active, autonomous, responsible and self-regulated person. These are very important due to the varying demographical backgrounds of participants of MOOCs. These participants are heterogeneous, with varying motivations for participation. The pedagogy employed for a course should depend on the discipline irrespective of course elements, learning outcomes assessment, interaction design and curricular context (Neumann et al., 2002).

2.6.2 Curriculum structure

Academic disciplines shape the content, teaching style and thus how students learn or engage in the classroom (Umbach, 2007). Educationists use two approaches to categorising disciplines based on Biglan's framework and Holland's theory of occupational choice. According to Hiller and Nelson Laird (2021), Biglan's three dimensions divide disciplines into hard/soft, pure/applied and life/non-life categories. This result in the eight categories is shown in Figure 2-2. However, Holland's theory classifies disciplines into realistic, investigative, artistic, social, enterprising and conventional. Holland deals with that personality type leading to career choice and ultimately resulting in people's personalities being more in sync with each other (based on their values, interests and abilities).

	Hard		Soft	
	Life	**Non-life**	**Life**	**Non-life**
Pure	Biology, Biochemistry, Genetics, Physiology, etc.	Mathematics, Physics, Chemistry, Geology, Astronomy, Oceanography, etc.	Psychology, Sociology, Anthropology, Political Science, Area Study, etc.	Linguistics, Literature, Communications, Creative Writing, Economics, Philosophy, Archaeology, History, Geography, etc.
Applied	Agriculture, Psychiatry, Medicine, Pharmacy, Dentistry, Horticulture, etc.,	Civil Engineering, Telecommunication Engineering, Mechanical Engineering, Chemical Engineering, Electrical Engineering, Computer Science, etc.	Recreation, Arts, Education, Nursing, Conservation, Counselling, HR Management, etc.	Finance, Accounting, Banking, Marketing, Journalism, Library and Archival Science, Law, Architecture, Interior Design, Crafts, Arts, etc.

Figure 2-2.Biglan's classification of disciplines

Source. Goel (2010).

The first dimension (hard/soft) demonstrates the discipline's consensus about the extent and scope of problems and the best investigation technique. The second dimension (pure/applied) distinguishes domains by whether the study applies practical problems or not. The third dimension (life/non-life) indicates whether the discipline studies life or inanimate/inorganic things. Most studies on disciplinary variations in students' learning styles uses Biglan's hard/soft and pure/applied dimensions (Hiller & Nelson Laird, 2021). Like any other course, the curricular structure of a MOOC also depends on the discipline of focus. However, with MOOCs, the classification by specialisation usually uses the STEM (Sciences, Technology, Engineering and Mathematics | Medicine) & and non-STEM (Arts, Business, Social Sciences, Humanities and Education) dichotomy. MOOCs based on STEM are hard MOOCs, while those that deal with non-STEM are soft MOOCs (Najafi et al., 2017). Swan and colleagues observed that education that emphasises the development of knowledge rather than the transmission of it is a hallmark of non-STEM courses (Swan et al., 2014).

Regarding "soft MOOCs," discussion and exposure to various viewpoints are encouraged. However, in the case of "hard MOOCs," questions and answers time are given greater emphasis. Furthermore, courses associated with hard MOOCs tend to have structured and sequenced content, with those for soft MOOCs having structured content and showcasing more of a spiral curriculum (Najafi et al., 2017). In this regard, the curriculum context of MOOCs should be constructed so that disciplinary characteristics and expectations are considered. Some attributes of expectations as per STEM and non-STEM disciplines leading to the stated pedagogical approaches identified by Najafi et al. (2017) are summarised below:

- Soft MOOCs foster a critical learning perspective by allowing opposing paradigms to coexist. Hard MOOCs encouraged idea and skill mastery.
- Soft MOOCs emphasised critical thinking, evidence-based reasoning and evidence assessment. Hard MOOCs emphasise understanding core ideas and methodologies and applying them to problem-solving.
- Student-centredness is more pronounced in soft MOOCs than in hard MOOCs. Discussions on pre-existing pedagogical materials might inspire the development of brand-new material. Students actively shape course content through their own content creation, expanding upon teachers' initial goals. Thus, tangential discussion and opportunistic expansion exist for soft MOOCs, which is difficult in the case of hand MOOCs. It is the responsibility of facilitators to provide leadership.

Learning in the digital age, where technology is inevitable, is effective with a proper mix of sound pedagogy and appropriate technology. The critical ingredient to MOOC learning should be well-established teaching methodologies that properly intersect with technologies. MOOCs were initially designed for the world to have a "bite of academic treats" of ivy league universities. However, they are being used by either the same universities or different universities to integrate their classroom courses. The latter use of MOOC is the focus of this study. Primarily, MOOCs were designed purely for online learning environments adapted to the classroom environment. Similarly, xMOOCs as online courses started as an offshoot of the traditional campus-based courses. Thus, blending MOOC as a product should be seen and treated as quite different from the basic building blocks of the classroom and MOOC. In this respect, specific design considerations should be made for this blend to be efficient and effective. Its design should be seriously considered in blending MOOC and campus-based courses (Govindasamy, 2001).

2.6.3 Assessments

MOOCs are online learning opportunities that combine teaching, learning and assessment. The primary goal of assessment is to enhance students' learning and instructors' teaching as both respond to its information. Assessment as learning (wherein students use feedback from instructors, peers, and self-evaluations to boost their confidence and knowledge) is just as valid as assessment of learning (summative) or assessment as learning (formative). Incorporating assessments with peer- and self-assessment opportunities at the end of each week or unit for a MOOC is a widely recommended strategy for promoting learning (Cox et al., 2014). However, it is challenging to ensure that cheating does not occur, though apps like Invigilator are preventing online cheating. MOOCs' assessments come in objective tests and essay assignments. For objective questions, the provided answer may be examined and scored automatically. For essays, peers manually marked them using a rubric to analyse and grade the submission. The graded assessments with feedback are mandatory activities for certificates to be awarded on completion. Each learner's assessment is randomly given to a couple of other learners to grade and the average grade is computed and awarded to the learner. Learners receive their marks upon grading others. Peer assessment allows large-scale assessments and encourages critical thinking and active learning. Peer assessment is collaborative and scalable, but its legitimacy is questioned compared to lecturers' or professors' summative judgement. Peer grading as a substitute for professional review requires rubric design, learner assessment criteria training, and grading discrepancy resolution. So, while peer grading can enhance traditional assessment methods, it requires careful installation and periodic validation against expert judgements to assure its usefulness and fairness as a summative assessment approach in MOOCs.

The knowledge journey from the start (stating or specifying the learning aims and objectives) to its end (assessment of the objectives) comprises many things aside from the three already discussed–learner-centredness, curriculum structure and assessments. The rest will be addressed from this paragraph forward.

2.6.4 Duration

MOOCs range between 1 and 16 weeks in length. However, the typical duration of a MOOC is 1-6 weeks (mini-MOOC) or 6-10 weeks (full-MOOC). The typical time commitment for completing a MOOC is one to two hours per week, making it ideal for learners with busy schedules. As they progress through the course, participants move at their own pace through the material and interact with a global learning community. In most MOOCs, the teaching strategy involves producing short lecture videos. The videos' duration is usually 5-10 minutes to introduce fundamental concepts of the topic for the week/unit; however, research shows a video within 6 minutes is the best.

2.6.5 Content

The main content of MOOCs comprises a series of web pages or files in the form of portable document formats (pdfs) and videos either in the same domain or from different disciplines. The asynchronous delivery of this curriculum's content allows students to access it whenever and however they want, considering their learning styles, paces, social commitments and time zones.

2.6.6 Textbooks

Traditionally, procuring textbooks is not required for MOOCs since all readings are provided within the MOOC content or to open access texts licensed under a Creative Commons Attribution (*i.e.*, CC-BY-SA 2.0). The rationale for this singular act is to keep access to MOOCs as open and accessible as possible. That is why most MOOCs 'suggest' learners read owned textbooks or extensively 'consult' the web, significantly "beyond the google search tools". In line with the openness of education or open access movements, publishers and universities produce copyrighted but free textbooks. MOOC learners can check sources such as World Knowledge Inc and the University of British Columbia, which legitimately offer textbooks for free. However, different modalities exist for MOOCs that refer to or use textbooks, especially regarding licensing with publishers. Three options can be identified, which are described in the following paragraphs.

- Open textbooks: Textbooks are created as Creative Commons with CC-BY-SA 2.0 Attribution by publishers. An example of such an arrangement is Saylor

(MOOC provider) which produces its supplementary textbooks licensed under Creative Commons Attribution through funds provided by the Saylor Foundation.

- Textbook with a publisher providing on-screen reading only: Some MOOC providers have partnered with publishers to offer portions of specific textbooks free for learners enrolled in the courses. MOOC provider Coursera, for instance, has partnered with publishers including Cengage Learning, Macmillan Higher Education, Oxford University Press, SAGE and Wiley in this respect (Anderson, 2013). The course materials are available through e-readers. The deal is a win-win for all parties–learners, instructors and publishers. While learners can read the material on-screen, they cannot be able to print or download these free textbooks. Instructors who hitherto were restricted by contractual agreements with publishers to the extent to which they can use their textbook available to learners in what they could ask learners to read. Students interested in obtaining copies of the publishers' books may buy complete copies of such books from the publishers.
- MOOC Provider and Publisher providing open-access book. MOOC providers partner with publishers whose textbooks are made accessible to those enrolled in the MOOC. An example of this model is Elsevier's provision of textbooks to edX MOOCs. As part of the resources provided for the MOOC, Elsevier discounts participants on the print or electronic version of the required textbook (Elsevier, 2013). Another example of a book publisher-MOOC provider partnership is Federica Web Learning and Springer Nature via MOOCs initiatives at Springer Nature (Springer, 2017). With this initiative, MOOCs are designed with accompanying textbooks together from the outset, i.e., creating MOOCs based on textbooks and vice versa.

2.6.7 Pedagogical strategies

MOOCs' instructional design borrows from e-learning. Formats include instructional videos, videos with quizzes, automatic and peer-or self-assessment and online discussions. Furthermore, "cMOOCs offer excellent opportunities for non-traditional teaching approaches and learner-centred pedagogy in which students learn from one another" (Swan et al., 2014, p.23). The two pedagogical approaches adopted for xMOOCs are cognitive-behaviourist and social constructivist (Rodriguez, 2012). Many MOOC sites use cognitive-behavioural teaching strategies (e.g. Udacity, EdX and

Coursera). Cognitive-behavioural MOOCs are identified by 1) using forums where students can ask questions about course content and tests; 2) having instructors whose jobs are the same as those of face-to-face teachers; and 3) having little interaction between students and instructors (Rodriguez, 2012). Social constructivist MOOCs, such as those offered by FutureLearn and iversity, use social tools for communication. They do this through forums and lesson discourses to support the co-creation and co-evolution of learning content (Rodriguez, 2012).

2.6.8 Discussion forums

Besides studying the recommended materials, learners participate in discussion forums for information-seeking and learning. "Message board," "conversation group," and "internet forum" mean the same thing. Students may post, reply to, read, rate and view forum posts (Wong et al., 2015). These asynchronous discussion forums provide an avenue for interaction (e.g., instructors-learners or learners-learners) or for learners to post questions that others (facilitators but preferably peers) answer. Forums are a default feature of MOOCs; thus, teachers widely use them as educational tools in MOOCs. However, learners' participation in them is usually optional, though mandatory with others if a certificate on completion is desirable. Learners may publish three types of messages in a discussion forum: threads, posts and comments (Wong et al., 2015). They further define the three levels of a discussion forum as follows:

- threads are the initial forum topics;
- posts are the message within the thread;
- comments are replies to a post or another comment and
- Messages result from interaction with participants within the discussion forum (Wong et al., 2015).

Given the enormous learner population in MOOC, interactions and conversations among themselves and the instructor(s) are extremely limited compared to online and campus-based regular courses. Commenting on academic uses of discussion, Wong et al. (2015, p.12) asserted that:

> the interactions of students in online forums contribute to their education. Discussion forum interactions like this are active learning since they include pursuing knowledge.

Students' engagement with forums in online courses tends to aid student learning. Instructors should use the discussion forum to curate views, ascertain whether learners understand the contents and meet the lesson objectives. As they examine the discourse within a forum, instructors can identify content areas that need to be expanded upon and clarified concerning the learning objectives.

2.6.9 Live chat

Another optional activity, which is uncommon for the massive population of MOOCs, is synchronous events. Examples are ‘live’ webinars (interactive sessions) or ‘live’ chats, requiring participants to join at specific dates and times. The sheer number of participants and their diverse time zones make synchronous activities unusual in MOOCs. With live chat, the time zone constraint requires participants to be grouped according to time zones or closeness to parts of the day –dawn, morning, mid-day, afternoon, dusk, evening and night. Again, the recommended maximum participation threshold for an effective ‘live’ chat is twenty-five per group. Moderation is preferred in such instances, with summaries of interactions and decision outcomes produced and communicated at the end of the session.

2.6.10 Email

Email is an essential and widely used communication medium, but its use within MOOCs is restricted. This restriction may be due to the lack of response to the growing influx of information facilitators receive and the low response rate to emails sent to them. Most MOOCs use emails to introduce participants to the learning community and environment, provide an essential ‘housekeeping’ announcement, provide closing remarks and formally dissolve the community at the end of the MOOC. Most of the tools used for interaction within online learning environments employ emails to confirm transactions for future reference. That is, these tools, by default, send emails of one’s threads, posts, comments, messages, file uploads and the like as emails for safekeeping. These emails can be used for forensic evidence of one’s participation, as most MOOC platforms do not keep enrolled users perpetually. Emails also provide individualised and personalised information regarding the lessons and encourage lurkers and less active learners to engage with the course. However, due to the massive number of learners in

MOOCs, the ratio of learners to instructional team members is usually significant; it does not allow frequent personalised email feedback (Najafi et al., 2017).

2.7 Technologies used for MOOCs

As in online learning, MOOC mainly uses ICT to deploy content and interact with the users wherever they are. Thus, ICT plays an essential role in the delivery of MOOCs since it is the medium through which the facilitators and learners meet to share information and transfer knowledge. In this regard, technology is vital to the success of MOOCs since technology is inevitable in MOOCs. The hard skills needed to successfully include digital literacy, information literacy and the ability to use social software effectively.

MOOCs' toolbox includes Learning Management systems (LMS), social media (Facebook, Twitter, among others) and other social tools (WhatsApp, Telegram) (Epelboin, 2015). Three technological options exist, whatever type of MOOC is deployed (Yuan et al., 2014), as depicted in Table 2-2.

Table 2-2:MOOCs' Technologies and Institutional Implications

Options	**Example technology**	**Course Provider**	**Benefit**	**Revenue**	**Copyright**
Open up existing VLE	Blackboard, Desire to Learn, & Moodle	Any institution	High level of control over activities	Maintain data and associated revenue streams	Educator with institution
External MOOC platforms	FutureLearn , Coursera, Udacity & Edx	Predominantly elite universities	Less institutional disruption, external marketing	Data and revenue streams shared with the provider	Platform asserts rights
Use ad hoc platform	MOOC.org, WordPress, & Google	Educational innovators	Flexible and open to anyone for	Focus on innovation and	Educator

for innovation	course-builder		experimentation	organizational Learning

Source. Yuan et al. (2014)

2.7.1 Using learning management systems

Learning management system (LMS) is a software or app that provides the platform for e-learning and serves as the administrative foundation for e-learning. It is often used interchangeably with virtual learning environments (VLEs) and course management systems (CMS). LMS serves as a centralised channel for interaction between the teacher and the student and a repository for papers, conversations, assignments and evaluations. It also provides learner analytics or metrics, such as reading a lecture or analysing discussion comments, to assess whether a student's behaviour is linked to course performance. Higher education institutions (HEIs) have provided opportunities for online learning by using this software app or application, either locally on their network or as a service (SaaS) cloud solution. The primary purpose of LMS is to provide a one-stop-shop for educational resources; however, its true potential lies in providing learner analytics or metrics. MOOCs are online learning environments that mimic the closed environment of traditional education environments. These LMS makers have solutions that make MOOC teaching possible by providing extra features such as advanced analytics and big data capabilities. Blackboard's CourseSites has offered courses since April 2012; Instructure launched its Canvas Network in November 2012. In September 2013, Moodle offered a MOOC on its LMS MOOC platform, while Desire2Learn presented its inaugural Open Course in August 2013. With further re-configuration, Providers could use these software apps to host MOOC activities (Yuan et al., 2014). Institutions with Blackboard Learn can access the MOOC platform without paying for the extra features, with instructors having the privilege of mounting concurrent MOOCs limited to five courses (Sheridan, 2013; Yuan et al., 2014). This option is an easier transition for faculty and students moving to MOOC.

2.7.2 Using MOOC Platforms

MOOC platforms are online learning systems that are designed with features and tools aligned to the learning strategy. Examples of these platforms include ALISON, Coursera, edX, FutureLearn, iversity, Khan Academy, Udacity and Udemy. These

MOOC tools are owned by either commercial entities or non-profit organisations, using a different financial model for sustainability. On these platforms, courses are mounted without the usual pre-requisite of academic classes and are accessible without fees to anyone anywhere and anytime. The participant must be digitally literate, have internet connectivity and be willing to learn the course. MOOCs are being used in three different ways (Reich, 2013):

- MOOC as an LMS. MOOC serves like a typical LMS platform like Blackboard, Canvas LMS, or Moodle, which are used to develop online courses and then host the course. An example is OpenEdx, Canvas Network.
- Self-contained MOOC. This standalone online course is a learning hub that comprises content and assessment infrastructure. Here, students enrol on the course and study content from start to finish without teacher interaction. An example is Alison and Khan Academy.
- MOOC as a digital teaching platform. This platform contains pre-populated content and learning objects with videos and assessments; however, it is designed to be used by students in a classroom with a teacher. This pre-fabricated course containing contents could be sold to institutions or downloaded and used as OERs. Third-party organisations use them in the same manner as textbooks. It may be ideal for a flipped class where the F2F is used for lectures or case study discussions. The blended MOOCs for this study are of this type, where UCC students enrolled into selected MOOCs by the lecturers.

The cost of publishing MOOCs comes from development, production, teaching, Internet connectivity, server, software and hosting, although this varies among platforms. The initial cost for a university to use edX to provide a single course is around £160,000, enabling the institution to set up its "production studio" with an additional amount of £22,000 charged for each extra course (Kolowich, 2013). How many HEIs in the global South have the financial resources to afford high-quality online materials development courses? That is why the opportunity afforded by blended MOOCs should be taken seriously and utilised by tutors from the global South to introduce digital learning among their students. The LMS and MOOC markets overlap, and the two will merge sooner than later. Daphne Koller, the co-founder of Coursera, believes that blended learning and MOOCs will represent the same thing, giving students a seamless experience transitioning from the "world of studying" to "the world of working". As of 2012, the Canvas Network is tied to the Canvas LMS (Hill, 2012).

2.7.3 Using Web 2.0 technologies

Web 2.0 tools are web apps that enable users to generate web content without knowledge of hypertext markup language (HTML). Examples of web 2.0 tools include blogging platforms such as WordPress and Blogger, social networking platforms such as Facebook, LinkedIn, Google+ and WhatsApp, as well as wikis such as Wikipedia, Wikibooks and WikiEducator. MOOCs are online courses that are deployed using web 2.0 technologies. From Liyanagunawardena et al. (2013), the first massive open online course (MOOC) was a seminal course on Connectivism and Connectivist Knowledge (CCK08) that was facilitated by George Siemens and Stephen Downes in the year 2008. A wiki and blog were used to host the structure of the course with asynchronous and synchronous communication, respectively, done on Moodle’s discussion boards and Elluminate/Skype (using UStream).

Other tools included Twitter, Second Life, Pageflakes, Facebook, Google Alerts, Google Maps and Netvibes. Twelve different tools were used (Fini, 2009, as cited in Rodriguez, 2013). The most important details in this text are the use of multiple tools as a learning environment, the disapproval of using LMSs, large, centralised and other institution-managed platforms to host online courses and the general-purpose, user-centred and user-owned characteristics of this approach. With this method, students utilise Web 2.0 tools they already possess to create and share material, collaborate and connect with other students while the course is still in session and available. Email or WhatsApp is used to call the group together and tags are inevitable to aggregate contents scattered on independent and separate platforms.

Multi-tools need to be used to distribute content on different platforms and learners’ existing resources and profiles are used, enabling them to merge their learning experience with their other ventures. Unlike the previous two, learners could be denied access to the content after a certain period. The use of multiple tools as a learning environment stems from the disapproval of using LMSs, large, centralised and other institution-managed platforms to host online courses. Online course designers using this strategy should avoid overloading students with too many or unnecessary technological tools since this can impede the learning process.

2.8 Blended MOOCs

MOOCs are an offshoot of online education that can incorporate most in-class learning activities, except for practical sessions in the laboratory, which teachers must supervise Joshi (2015). MOOCs have led to a new breed of Open Educational Resources (OERs) emerging, which HEIs embrace in their on-campus courses resulting in blended or hybrid learning (Kloos et al., 2015; Zhang, 2013). This type of educational technology integration strategy has opened avenues for HEIs, especially those from developing nations with no online learning components, to have a feel of online learning through the blend mentioned above. Through this integration, MOOCs represent an excellent opportunity to revolutionise blended learning across all levels of education, including organisations providing continuous professional development (Ulrich & Nedelcu, 2015). MOOCs are expanding the possibilities for blended course designs in HEIs with their support for on-campus face-to-face (F2F), blended, or online courses (Bruff et al., 2013). MOOCs support the traditional education system, mainly tertiary, by blending MOOCs and classroom courses (Joshi, 2015). MOOCs also help in the classroom when they are licenced as the next generation of textbooks and become one of the tools a teacher uses to teach the course (TED, 2014, 13:09). A blended course is formed when a MOOC is combined with an in-class course or through different parts of different MOOCs. The Chief Executive Officer of edX, Prof Agarwal, hinted that academic institutions worldwide use edX's Online Campus to add new online courses quickly. Universities can use these resources from edX as additional course catalogues, especially for elective ones, to provide faculty with more learning resources and lifelong opportunities for university community members (Agarwal, 2020).

The terminology for the combination of MOOC and the on-campus course is currently contentious. Names such as blended MOOC (bMOOC/ B-MOOC), hybrid MOOC (H-MOOC), wrapped MOOC and distributed flip, among others, have popped up (Almutairi & White, 2018; Bruff et al., 2013; Koller, 2012; Yousef et al., 2015). Blended MOOCs represent an excellent opportunity to revolutionise blended learning across all levels of education, including organisations providing continuous professional development (Ulrich & Nedelcu, 2015). Blended MOOC is an EdTech in our current dispensation (Kloos et al., 2015); as such, educators should give their students the opportunities to use the best technology available to them at any given period.

Blending MOOCs are means of adapting MOOCs to local settings or localising them. Tutors should do the localisation in a manner as to avoid claims that MOOCs are a form of so-called "educational colonialism" or "neo-colonialism" from the elite universities in developed nations. Such a blend helps students to appreciate local, national and international issues around the subject matter, thereby enforcing the "thinking globally but acting locally" mantra"(Mohan, 2022).

Blending MOOCs are seen as a way of blurring the distinction among the various modes of learning — "campus-based", "online" and "distance". This blending that combines online (MOOC) and offline (classroom) into one whole learning package leads to a paradigm shift in how education is offered. Students do not need to attend physical lectures or listen to professors. Instead, they can do so by watching videos and doing interactive exercises at their own pace with colleagues locally or globally. Walters (2014) attributed the following possibilities that exist because of the blended MOOCs:

- Creating a vibrant education system of the future,
- Improving campus education,
- Unbundling content by moving away from a single source (Professor) to multiple sources (online, students, professors (when co-lecturing) and experts from the industry),
- Making it possible for students to take some courses locally at their enrolled university and others as MOOCs with content from different providers (institutions and universities),
- Causing the changing of classroom spaces from large lecture halls to small learning spaces. By letting students use online course materials and activities outside of class, blended learning allows for more personalised and self-directed learning.

Furthermore, blended MOOCs free most classroom time into on-campus classes, allowing students to engage in discussions and hands-on activities (Chen, 2013). The benefits of blended MOOC are optimising student engagement, satisfaction and, ultimately, learning (Bruff et al., 2013).

From Mazoue (2013), universities need to embrace this kind of blend as a matter of urgency and necessity because:

- Accredited institutions are accepting MOOCs as partial credit toward degrees.

- The MOOC-based curricula are leading to degrees from accredited institutions.
- MOOCs are challenging and displacing the financial model of educational institutions that rely on attracting and maintaining students for campus-based learning.

Blended MOOCs are ideal for institutions in the developing world due to a lack of adequate classroom facilities and insufficient lecturers. The effects are too many qualified applicants being denied admission and making more students clamped in a small lecture room with some standing, respectively. These undesirables would be a thing of the past, or their impact minimised once these institutions embrace the blended MOOC teaching techniques. This sort of blending is becoming the order of the day, especially in institutions that do not have e-learning support services.

Universities and tutors adopt blended MOOCs for various reasons, among which, according to Holotescu et al. (2014) are:

- Making students aware of the MOOC phenomenon and trends
- Enlarging knowledge/topics of the course, they have enrolled locally.
- Creating awareness of MOOC among lecturers.
- Serving to introduce e-learning to stakeholders of HEIs that do not officially use such technology.
- Introducing lifelong learning practice among students.
- Serving as a way of participating in open education (i.e., open access, OER) among stakeholders.
- Exposing students to teaching materials and pedagogies from other HEIs in different countries.

Joshi (2015) suggested that blended MOOCs can solve several of MOOCs' drawbacks. Well-known examples of blended MOOCs are:

- Learning Hubs model from Coursera.
- Kepler's combination of online information and in-person seminars in Rwanda.
- The U.S. State Department's MOOC Camp brings together online courses with in-person conversations at U.S. embassies and other public locations across the globe.
- Edx and San Jose State University, California, blended MOOCs on circuits and electronics (TED, 2014, 07:26).

2.9 The need for research in blended MOOC

The literature on MOOCs and their variants, such as blended MOOCs, belong to the broader fields of online education and e-learning. Thus, MOOC studies build and expand on the existing research knowledge in these fields (Gasevic et al., 2014). Also, learning through MOOCs belongs to the self-regulated or self-organised learning paradigm. Here, autonomous motivation is helpful for learners to achieve better learning outcomes (Zhou, 2016). Following an extensive literature review on adopting MOOCs, Guptaa (2019) observed that quite a few studies had examined students' behaviour towards MOOCs in developing countries. None of the papers mentioned has sub-Saharan Africa or Ghana specifically as the target audience of the research. Studying the acceptance and use of blended MOOCs in Africa will be a huge gain and cause a significant paradigm shift in human development on the continent. It will also boost the general or digital literacy levels of Africans. Despite MOOC's open access to everyone and anywhere, it has not been adopted by most countries in the global south, including Africa (Gunawardena, 2014; Mutisya & Thiong'o, 2021; Oyo & Kalema, 2014; Yunusa et al. 2021). Again, in a bibliometric review of MOOCs in Sub-Saharan African higher education, Yunusa et al. 2021, identified that the production of MOOCs is growing slowly. Furthermore, in systematic literature review Maphosa and Maphosa (2023, p.1) hinted that while industrialised countries have embraced MOOCs for technology-enhanced education, Africa still needs to catch up in adopting such platforms.

Authors such as Gunawardena (2014) and Veletsianos and Shepherdson (2016) have identified some reasons for MOOCs' lack of adoption/adaptation in the global south. Two primary concerns arise in the context of digital education. The first concern pertains to practical access, encompassing physical access to the internet and proficiency in digital literacy. The second concern revolves around cultural relevance, encompassing various aspects such as curriculum design, language, learning design, learner support, quality, authenticity, accreditation, institutional appropriateness, and cultural relevance. Yunusa et al. (2021) also identified poor internet connectivity, a lack of policy framework, poor bandwidth and electricity, and a lack of staff with the right skills were the main things holding back MOOCs' growth in SSA.

Despite these, there have been calls for investigations on blended MOOCs at Higher Educational Institutions (HEIs) in the global south (Caulfield et al., 2013).

For the following reasons, blended MOOCs must be studied in depth as a means of delivering education on a global scale:

- To test how well-blended MOOCs work: Blended MOOCs have become increasingly common in recent years; however, there is little evidence to suggest that they are more effective than either face-to-face or entirely online courses. Therefore, studies must determine how blended MOOCs affect students' learning retention, enthusiasm and overall satisfaction. Blended MOOCs produced the same learning outcomes as regular courses but higher student satisfaction (Israel, 2015).
- As with any new form of education, there are obstacles to introducing blended MOOCs, such as creating helpful course content, handling student expectations and fixing technical glitches. More studies are required to understand further the difficulties that teachers and students may encounter (Chen, 2013). MOOCs have benefits and drawbacks for people in Asia and Africa due to cultural and language barriers (Chen, 2013). Although there were pedagogical and technological issues with MOOCs and worries about students' engagement, the blended MOOC successfully encouraged students to work together and provide constructive criticism.
- To investigate blended MOOCs' potential for combating educational disparities: Blended MOOCs can lower the educational barriers for people who cannot afford or travel to attend a regular classroom setting. Blended MOOCs have the potential to expand access to higher education and advance educational equity. However, more studies are needed to realise this promise fully.

Further grounds for investigating blended MOOCs in sub-Saharan Africa include the following:

- Few studies have been conducted on blended MOOCs in sub-Saharan Africa, despite the region's fast-expanding tech-adoption and education sectors. Further studies are required to address this knowledge gap and produce new information (Langthaler & Bazafkan, 2020).
- Sub-Saharan Africa provides a one-of-a-kind socioeconomic, cultural and educational backdrop. The local conditions affect blended MOOCs' success in this

region. This setting and its effects on blended MOOCs warrant more investigation (Chen, 2013).

- In some parts of sub-Saharan Africa, access to the internet, computers and mobile devices are severely lacking, creating a "digital divide." The digital divide hampers the popularity and efficiency of blended MOOCs. As a result, researchers must investigate how the digital divide affects blended MOOCs and investigate possible solutions.
- To achieve sustainable development, as is the goal of many in sub-Saharan Africa, better educational and occupational opportunities are needed. Blended MOOCs can be used to accomplish this. As a result, research on blended MOOCs' potential for long-term growth in the region is essential.

2.10 Blended MOOC and learning

Teachers are using blended MOOCs for many purposes. Blended MOOCs are used to accommodate students' diverse learning preferences. With this system, students can introduce new learning methods, such as flipped classrooms, while making learning accessible to those who may not follow traditional instructions. These strategies positively affect teaching and learning and are desirable that all should encourage and implement blended MOOCs. Morris (2014) notes that blended MOOCs supplement classroom instruction, providing students with tailored and individualised learning environments. These are not the only benefits of blending the classroom and MOOCs. Griffiths and colleagues, for instance, identified additional benefits of blended MOOCs: repetition of lectures, adding to or replacing secondary materials, filling in gaps in knowledge and showing students various instructional strategies and small group discussions and strengthening essential skills (Griffiths et al., 2015). Blended MOOCs also help mitigate some disadvantages typically highlighted by MOOCs, such as low completion and high dropout rates (Koller et al., 2013). Blended MOOCs improve learning processes and, as a result, enhance knowledge retention while also engaging learners and meeting their diverse learning needs and preferences (Bralić & Divjak, 2018). Blended MOOC encompasses blended learning, MOOC and classroom, with individual weaknesses. Though the strengths of some may negate the shortcomings of others, the resulting product–blended MOOC–has unique problems that designers must identify. Dalipi et al. (2016) indicated that MOOCs' efficacy and affordances (features and functions) make them a viable option for face-to-face pedagogies.

A TED Talk on why massively open online courses (still) matter by the CEO of edX, Anant Agarwal, indicated that a blended MOOC improves learning and understanding. Agarwal came to this conclusion when the failure rate for the "Circuits and Electronics" course fell from roughly 40 to 41 per cent every semester to 9 per cent. The failure rate decreased when the course was transformed into a blended MOOC through a partnership between edX and San Jose State University, California (TED, 2014, 07:26). Agarwal outlined additional components for blended MOOC success. These features are active learning, self-pacing learning, instant or immediate feedback, gamification and peer-to-peer learning.

1. **Active learning**: Students participating in active learning take an active role in the learning process or engage with the learning process in various ways. This learning is in contrast to passive learning, which comprises students just sitting in a classroom and listening to lectures. Actively involving students in their education increases the quality of their academic performance. Students will participate in classroom problem-solving, analysis, synthesis and evaluation activities through lessons comprised of interspersed video clips and interactive exercises. Such higher-order thinking tasks are required for university graduation. For MOOC, a learner may view a five- or seven-minute video on the topic and, then, do an interactive exercise on the MOOC platform. For blended MOOC, watching the video is followed by in-class activities such as group presentations, class discussion and debate, short written exercises, case studies and post-lesson quizzes.
2. **Self-pacing learning**: With regular classroom lectures, all students simultaneously receive the same stream of information, irrespective of an individual’s capability to assimilate and understand. Learning pacing can be very slow, slow, medium, quick and fast; thus, instructors should be cognisant of this absorption rate. Pace relates to the class's speed and is associated with how a learner feels as they progress through the sequence of activities in a class. Differentiating the speed of learning means that students’ progress at their own pace, which helps retain their attention and provides a developmentally appropriate level of challenge. For some advanced learners, this may entail

accelerating to advance to more advanced topics. At other times, they will want to slow down and delve deeper into the content's complexity. Differentiating the speed requires flexibility, responding to the learner's desire to move quicker or slower. Self-paced learning allows the learner to study at their own pace and schedule. The learner has complete control over the amount of content consumed and the time required to absorb the new information effectively. That is, learners can determine "what to learn," "when to study," and "how to learn." Students control the videos from the MOOC by pausing or rewinding them and checking them out from a book or web to ensure they understand the bit of content before proceeding. Learners' ability to revisit the lectures as often as they need enhances productivity and boosts learning retention. With a blended MOOC, the classroom session can be used for personalised learning or in-class active learning activities that further deepen understanding.

3. **Instant or immediate feedback**: Learners make queries when they need clarification on issues and immediate responses to the questions are necessary to enable them to progress in their learning. Instant feedback occurs when context-dependent information is provided "on-demand" in response to a learner's action while learning. As a learning tool, it helps students to improve their comprehension. Immediate feedback is needed for all activities–discussion forums, multiple-choice tests, or response boxes of MOOC learners. Formulae or 'correct code' are entered and checked automatically in it. They provide learners with rapid, automatic feedback on their responses. This feedback may be as fundamental as "right" or "wrong," or it can be more complicated depending on the verified response. Nonetheless, it is usually entirely automated in all circumstances. This method works well for testing facts, principles, formulae, equations and other conceptual learning forms with clear, correct answers. An immediate response to queries is not guaranteed in MOOCs due to the vast number of participants. However, for best practice, learners should get a response within 72 hours. As a formative assessment, computer-marked examinations can give participants immediate feedback on what they have learned and help them understand essential ideas better. The problem is that this evaluation type is unsuitable for measuring deep or "transformative" learning, creativity, or original thinking. The classroom session of the blended MOOCs can be used to make up

for these shortfalls of MOOCs. In Ed Bertschinger's opinion, instantaneous feedback makes it easier to turn teaching opportunities into learning outcomes. In addition, Kehrer et al. (2013) have emphasised and shown in their research that instant feedback is preferred to delayed input.

4. **Gamification**: It refers to adding game mechanics to non-game contexts (Deterding et al., 2011). Examples of non-game settings are the com pany intranet, a website and online communities. Gamification aims to engage participants to inspire collaboration, sharing and interaction. In MOOC, gamification works by providing proactive directives and feedback to the learners by adding game mechanics and game dynamics to MOOC platforms, resulting in the performance of learning goals and objectives. Examples of game mechanics are rules and rewards such as points, levels, missions, leader boards, badges and progress. In contrast, the collection of feelings, behaviours and desires having particular meaning with people and inspired by game design are examples of game dynamics. An engaging gamification experience elicits an emotional response from the participant. This showcases the most effective activities an audience can engage in to contribute to shared objectives collectively. Gamification is a highly effective strategy for increasing learners' motivation and performance. Gamification increases user engagement and motivation, with users becoming productive and solution-oriented due to increased interest in the tasks they created. Gamifying teaching boosts academic performance. As a result of applying these gamification techniques to education, online laboratories can be made, thereby instilling creativity and problem-solving among learners (TED, 2014, 11:13).
5. **Peer learning**: This is a way of learning in which people learn from and with each other. Peer learning is an educational practice where students collaborate to accomplish educational objectives. The interaction of students in the same class or study group, student-run seminars, cooperative learning and group projects are examples of student collaboration. When working with their peers, students are more comfortable. They are more inclined to interact, reflect and explore concepts more deeply than they would in a teacher-led setting. It is learning by teaching. Some benefits are that the students can work together and communicate better. They will have more self-confidence because they can care for their learning. With a supportive network comprising learners, MOOCs provide students with

the opportunity because students learn more effectively when they engage with one another. Discussion boards, social networking sites and Twitter are used to increase learners' engagement by allowing them to create knowledge and views based on information and conversations. Peer learning at its most extreme is found in cMOOCs, a more flexible, genuinely open and learner-initiated form of MOOC. This kind of learning belongs to the learning theory known as connectivism. A connectivist learning environment is one in which learning occurs across multiple knowledge sources that are not entirely under the control of an individual (Downes, 2012; Siemens, 2004) and actual 'peeragogy' (Rheingold, 2014). With connectivism, learning is not just about what an individual knows but also about where the individual can find knowledge. "Know-where" is a part of "know-how" and "know-what" as aspects of knowledge and it is just as important as the other two. For newcomers to connectivism, it may be confusing and overwhelming as they work across multiple media simultaneously. In contrast, experienced learners find learning above and beyond what was previously taught in formal education exciting because they are liberated to learn for themselves and by themselves with the assistance of other learners (Purser, Towndrow & Aranguiz, 2013). True connectivism reduces human contact and increases computer usage, resulting in less meaningful interactions and less time building social skills. This situation is where blended MOOCs come in, combining online learning with in-person classroom settings to foster actual face-to-face interaction and the development of social skills.

2.11 Students' Engagement

Researchers employed many indicators to predict learning and measure students' engagement in various situations. These engagement-related indicators are examined from a single point of view, operationalised through students' participation in multiple activities. Engaging in discussion forums (Wang et al., 2015), watching video lectures (Whitehill et al., 2015), or participating in course evaluation activities are often measured in terms of the number of contributions (Joksimovi et al.,2017). Hodges (2018) defined engagement as assessing one's level of engagement, enthusiasm and commitment to a company. The organisation could be a school or a classroom where pupils must actively participate in the activities. Engagement is described as energy in action, the connection between a person and the exercise they perform for a stated goal in academic settings. So, a student's active participation in a task or activity is vital for the occurrence of engagement. Engagement is among the most accurate predictors of academic performance (Lei et al., 2018). School completion rates and lower-risk behaviours allow students to leave the learning community (Archambault et al., 2019). By and large, engagement is the thought, action and commitment a student invests in the things students do to achieve successful students' goals within an educational setting. According to Dixson (2015) believes that engagement can be defined as the active involvement of students in their educational pursuits, encompassing the allocation of time, energy, cognitive processes, exertion, and, to some extent, emotional investment (p. 146). This definition accounts for learners' activities within a course and learners' motivations and emotions connected to their learning.

Student engagement covers the range from disengaged to engaged at various levels within which the same student may display varying degrees of engagement (Bryson & Hand, 2007). Ideally, learning improves when students are engaged, while learning declines when students are disengaged. Student engagement indicates successful classroom instruction and a desirable lesson outcome for all schooling systems. Students are more likely to do well in school and reach their educational goals if they do things that make them active. Students persist steadfastly despite academic challenges when engaged. Moreover, engaged students have hurdles that confront the assigned task; with enthusiasm and diligence, they delight in their learning activities as they aim to attain mastery. On the other hand, when students passively listen to and take notes as lectures go on with little or no interactions, they become disaffected. Skinner and Belmont (1993, p.15) characterised disaffected students as follows:

> they are passive, do not put in much effort, and give up easily when things get tough. They might be bored, sad, anxious, or even angry because they have to be there for class. Furthermore, they may disengage from learning opportunities or demonstrate rebellious behaviour towards teachers and peers.

Students' disengagement or disaffection may lead to casual or drastic withdrawal from the lesson's activities. Generally, disengaged students acquire only a tiny amount of knowledge; therefore, facilitators and tutors must ensure that students gain enough experience, which enhances knowledge acquisition. Active students have three things in common: they are interested in their work, keep going when learning gets hard and feel fulfilled when all tasks are accomplished (Schlecty, 1994). More student participation leads to better teaching methods, which helps students learn more about the subject (Coates, 2006).

In blended learning mode, universities use new technologies like lecture recording, online chat, discussion forums and social networking sites to get students more involved. In all learning contexts, students' engagement is an essential ingredient that the designers and facilitators must consider (Henrie et al., 2015, Kim et al.,2019). An e-learning environment provides students with tools that assist their learning and offers more opportunities for engagement that foster better academic performance (Kim et al.,2019). The level of class participation determines how students perform in school (Kim et al.,2019). Jung and Lee (2018) discovered that learning persistence was directly associated with the presence of instruction and its ease of use. The relationship between learning perseverance and these three factors is mediated by academic self-efficacy, teaching presence and the sense of being useful. Between "engaged" and "disengaged," there is a continuum of student involvement and "engaged" can mean different things at different levels (Bryson & Hand, 2007). This assertion agrees with Schlechty's levels of engagement framework, shown in Table 2-3

Table 2-3:Schlechty's levels of engagement and their characteristics

Engagement types	Characteristics	Attention	Commitment
Authentic Engagement (Highest level)	Persistence, continuous inquiry, self-direction, playfulness with content, and the ability to share understanding without being asked to do so.	High attention	High commitment
Strategic compliance	There is apparent effort, some originality, and a focus on getting the job done to meet norms that come from the outside.	High attention	Low commitment

Ritual compliance	People only put in a small amount of effort to lessen "consequences" or other bad "punishers." There is no creative, curious, or willing to share what they know.	Low attention	Low commitment
Retreatism	Little to no work, progress, or effort; no curiosity, care, or interest in the content, collaborations, or task. Neither productivity nor results are improving.	No attention	No commitment
Rebellion (Lowest level)	Zero demonstration of learning; outright disruption & defiance	Diverted attention	No commitment

Source: Heick,2019; Spencer, 2017

Schlechty's levels of engagement classify students' engagement by utilising two fundamental concepts: attention and commitment. Examining student engagement and exploring its implications for authentic student involvement in the learning process are valuable endeavours. The five levels of student engagement by Schlechty (2002) are explained in the ensuing paragraph.

- Authentic Engagement: Students are willing to stick with an activity even when it is hard, which shows that it is essential to them. The main goal for students is to do well in the activity.
- Strategic Compliance: Students value the work because of marks, grades, class rank, the teacher's approval and the respect of their peers. They will stop doing it if they do not get these extra benefits.
- Ritual Compliance: A student only wants to learn to avoid getting a bad grade or mark. The most important thing for these students is to avoid getting in trouble with their teachers and getting into fights with other students.

- Retreatism: Retreats are students who do not care about what is going on in class and do not show any emotion. They think they cannot do the task and meet the expectations because they do not have the skills to perform it or do not see why it is essential.
- Rebellion: Students do not do their work and do things to bother others. They develop a bad attitude that sometimes makes other people rebel as well.

People sometimes use the words "student engagement" and "student motivation" to refer to the same thing, but they are not. Motivation is usually the internal and long-term drive of the student. At the same time, engagement responds to an external and immediate satisfaction of a need. An individual may be highly motivated to learn a discipline but may find an activity in one of the lessons tedious, thus becoming disengaged. However, Hufton et al. (2002) believe that high levels of engagement show high motivation levels. Students' engagement deals with various variables, including intellectual, emotional, behavioural, physical, social and cultural engagement (Student Engagement, 2016). The development of a classroom student engagement measure was undertaken by Handelsman et al. (2005). Four indicators were identified that demonstrate students' allocation of time and exertion within the classroom setting. These are indicators of how learners invest themselves academically:

- Dedication to improving one's skills (through continued study and practice).
- Emotional involvement or making the course interesting and relevant to the students' life.
- Involvement and interaction (i.e., having a good time while contributing to informal discussions).
- Preoccupation with performance (in the form of high-test scores and final grades) (Handelsman et al., 2005, p. 187)

In reality, student engagement is a complex issue. Researchers have yet to reach a consensus on its definition and dimension. The engagement dimension deals with the various components or subtypes comprising students' engagement, i.e., different versions of its makeup. Table 2-4 shows other authors' definitions and dimensions of student engagement.

Table 2-4:Examples of variations in definitions and dimensions of engagement

Authors	Construct Name	Definition	Dimensions
Audas & Willms (2002)	Engagement	The level students engage in academic and non-academic activities and how much they understand and value the study goals.	
Schaufeli, Salanova, Gonzalez-Rom, & Bakker (2002)	Study Engagement	A satisfying and good study-related mental state marked by concentration, enthusiasm, and commitment.	3– a) Vigour; b) Absorption; and c) Dedication
Willms (2003)	Student Engagement at School	Students care about how well school goes and how much they like and take part in school activities, both academic and not.	2–a) Behavioural and b) Psychological
Coates (2006)	Student Engagement	Students put reasonable effort into activities that help them learn and lead directly to their desired results.	2–a) Academic and b) Social
Christenson, Reschly, Appleton, Berman-Young, Spanjers & Varro (2008)	Student Engagement	Students' investment in and love for learning, school belonging and identity, institutional participation, and initiating activities to attain a goal.	4– a) Academic; b) Behavioural; c) Cognitive; and 4) Psychological
Skinner, Kindermann, & Furrer (2009)	Engagement	The quality of students' participation or connection with the schooling endeavour and hence with activities, values, people, goals, and place.	2–a) Behavioural and b) Emotional

Source : Alrashidi et al. (2016, p.42)

From, Table 2-4 the conclusion is that there is no consensus on the dimension of engagement. However, Redmond and associates identified five dimensions for an interdisciplinary, higher education online learning environment (Redmond et al., 2018), shown in Table 2-5.

Table 2-5: Overview of dimensions of online student engagement

Dimension	**Definition**	**Indicators**
Behavioural	Elements of a course are made to encourage desired behaviours, such as finding needed information, doing tasks on time, and taking part regularly.	1) Improving academic skills; 2) Recognizing opportunities and challenges; 3) Improving cross-disciplinary skills; 4) Improving self-direction; 5) Following the rules of online learning. 6) Helping and cheering on other people
Cognitive	"The active learning process" (p. 191) means the student must interact with the course material, skills, and assessments.	1) Critical thinking; 2) Activating metacognition and integrating ideas; 3) Justifying decisions; 4) Learning a lot about a subject; 5) Sharing knowledge
Collaborative	Students participate in an online course by doing tasks together, talking about them, and working together.	1) Learning with other students; 2) Getting to know teachers; 3) Linking up with opportunities at institutions; 4) Making professional connections
Emotional	Students' positive and negative emotional responses to learning. Such responses include values, interests, feelings, enthusiasm,	1) Handling expectations; 2) Stating assumptions; 3) Figuring out what drives people; 4) Making a promise to learn

	expectations, motivations, and commitment.	
Social	Students' relationships with one another, community spirit, a feeling of belonging, mutual understanding, trust, and respect.	1) Bringing people together; 2) Making people feel like they belong; 3) Building relationships; 4) Building trust

Source : Redmond et al. (2018, p.190).

Both Table 2-4 and Table 2-5 indicate the multidimensionality of student engagement in face-to-face, blended or fully online environments. After a lengthy discussion of student engagement, it will be prudent to focus the discussion on the importance of students' engagement at this juncture. "Education encompasses much more than preparing pupils to work in the future. The objective of education is to assist everyone in achieving their full human potential" (Meredith, 2014, para. 12), leading to being productive and having a meaningful life. However, the beginning of the journey of attaining this goal is through learning, of which engagement is vital. Gallup's (2018) study, 'School Engagement Is More Than Just Talk,' discovered that

> Engaged children are 2.5 times more likely to report receiving outstanding grades and performing well in school. They are 4.5 times more likely than their actively disengaged peers to be optimistic about the future. Teacher engagement strongly correlates with absenteeism and employee turnover and is a crucial driver of student engagement (Hodges, 2018, para. 12).

Bernstein (2021) highlighted the following: Citing another Gallup study on engagement.

- Engagement has a measurable positive effect on student growth.
- Schools with a high student engagement better prepare children for the future.

The significance of student participation in course materials, classmates, and the teacher is reemphasised by social construction and the CoI paradigm. Higher levels of student involvement have been linked to better learning outcomes (Martin & Bolliger, 2018). Grey and DiLoreto (2016) emphasise the significance of actively involving learners to promote satisfaction and perceived learning outcomes. This link emphasises the need to examine the connection between learner engagement, satisfaction, and academic success in our study population. This link emphasises the need to examine the connection between learner engagement, satisfaction, and academic success in our study population. Students' participation is correlated with their satisfaction with their educational experience for the first time. According to research by Price and Tovar (2014), higher graduation rates at institutions can be attributed to students' increased motivation. Despite the benefits of engagement, there is evidence that most students are not engaged. This lack of engagement is apparent, with drop-out being the topmost. Regarding disengagement, the 2018 Gallup Poll made the following observation (Hodges, 2018, para. 24).

> Almost half of the students (47%) are engaged, 29% are uninterested, and 24% are disengaged. As they advance along with the educational system, students become less engaged.

This research on student engagement in blended MOOCs is an essential expansion of the existing literature on blended learning. The study recognises the fundamental research while addressing deficiencies (e.g. inconsistent findings) and implementing these principles in a fresh, contextually appropriate environment (i.e. University X). The results of this study will not only enhance the intellectual discussion but also offer practical insights for effectively incorporating blended MOOCs in higher education. From what has been discussed, student engagement is one reason student satisfaction and performance vary greatly.

2.12 Student engagement in MOOCs

The instructional delivery model or strategy in an online setting is a complex phenomenon affected by various factors inside and outside the online learning environment. Researchers have identified many factors impacting students’ engagement in online learning, among which are:

- Learner attributes, among many others, self-efficacy and self-regulation are already present (Strang, 2017).
- The amount of involvement an instructor has in a class, such as the time an instructor spends developing course content, how an instructor provides feedback, and the rate at which conversations occur (Jaggars & Xu, 2016).
- The course design strategies include flipped classroom/cooperative learning and facilitated/self-paced (O'Shea et al., 2015).

Participants of MOOCs do not generally engage with MOOCs as they do with traditional online courses in which the assumption is active participation and interaction (Swan et al., 2014). The specific goal of those enrolled in MOOCs–who are well educated with a college degree, employed and participating in professional enhancement–is far different from those enrolled in traditional online courses.

Engaging students in MOOCs is a different "ball game" than making courses for the classroom or online learning. Here are some things that could have caused this to happen:

- Learners may not have the same goals for learning.
- Learners may not know each other.
- Learners may not be their peers.
- Learners are not required to finish the course.
- Learners have different reasons for signing up.
- Teachers have diminished direct observation of students' advancement and engagement.

Some people participate in MOOCs without ever taking a test or finishing one (Swan et al., 2014). Goggins et al. (2016) say that MOOC platforms have enough tools for many people to engage through social learning and interaction. However, De Freitas et al. (2015) hinted that engaged learning does not happen as expected. The simple reason is that people are not forced to engage if they do not want to or are not required to (Walji et al., 2016). Aside from this, people may not participate in MOOCs because of connectivity, digital skills, time zones, and how institutions handle power dynamics (Wu & Zhang, 2016). Though engagement is challenging in MOOC, it must be encouraged as much as practicable. When it comes to MOOCs, Wu and Zhang (2016) identified five characteristics that, in order of significance, boost student engagement:1) learning by doing problems with thorough explanations; 2) having an approachable and enthusiastic teacher; 3) having control over your own education; 4) collaborating with your classmates; and 5) making good use of the resources provided. Researchers employed multiple indicators of student engagement in MOOCs. Some factors mentioned in the studies are 1) time spent (hours, days and weeks) on course activities (e.g., viewing pages, engaging with quizzes and assignments); 2) the number of responses to other students' discussion posts; 3) the number of times students took part in course activities, such as a) how many videos they watched and b) they turned in assignments. c) how many topics were done, d) how well they were done, and e) how much credit they got toward finishing the course (Boyer & Veeramachaneni, 2015; Li et al., 2015).

2.13 Learning outcomes

In higher education, learning outcomes refer to the precise skills and information students are expected to gain and exhibit after successfully finishing a course or programme. They represent the expected conclusion of the learning process, encompassing the aims of education, such as perceived academic performance and student satisfaction (Eom et al., 2006). The significance of these results in evaluating the efficiency of online education systems is generally recognised (Graham & Scarborough, 2001). Student accomplishment and satisfaction are crucial learning outcomes that are significant educational quality markers (Doménech-Betoret et al., 2017, p. 4).

In this study, students' perceptions of satisfaction and academic performance constitute the primary learning outcomes under consideration.

2.13.1 Student satisfaction

Student satisfaction is complex, encompassing all aspects of the student's life, even pre-, peri- and post-study life. Appleton-Knapp and Krentler (2006) discovered that personal and institutional factors affect college student satisfaction. Personal characteristics include students' age, gender, employment, chosen learning style and GPA. Institutional aspects include instructor quality, feedback speed, expectations clarity and teaching style. Elliot and Shin (2002) created a comprehensive student satisfaction questionnaire with 11 characteristics and 116 indicators to assess higher education student satisfaction. These 11 dimensions are listed in the immediate paragraph.

The 11 dimensions or factors of satisfaction mentioned by Elliot and Shin (2002) are 1) the quality of academic guidance offered, 2) the friendliness of the student body, 3) the variety of extracurricular activities offered, 4) the availability of resources for students in need, 5) a genuine interest in, 6) the quality of teaching, 7) the efficiency with which financial aid is given, 8) the ease with which students can enrol, 9) the safety of the campus, 10) the quality of service provided, and 11) the use of students first strategies. A higher level of satisfaction will lead to better results. Because of the broad scope of student satisfaction, this study concentrates on student satisfaction at the micro level of the curriculum. Thus, a full-fledged student satisfaction model was not used in this study.

Consumers determine their level of satisfaction with a good or service by making an intellectual comparison between their expectations and the actual or perceived level of the product's or service's performance and other crucial aspects (Zeithmal et al., 1993, as cited by Elliott & Shin, 2002). Satisfaction happens when students think their performance met or exceeded their expectations.

In the same way, if expectations are higher than what is seen as a performance, this will lead to dissatisfaction. Johnson (1998, as cited by Elliott & Shin, 2002) found that perceived performance and expectations are related in a positive way, with expectations directly affecting perceived performance.

Students are said to be satisfied when they have a favourable subjective judgement of the results and experiences related to their education, as defined by Oliver and DeSarbo (1989 as cited by Elliott & Shin, 2002, p.198). Several things have been linked to student satisfaction in online classrooms, such as 1) how the course is set up and structured, 2) how involved the students are, 3) how the learners interact with each other, and 4) how present the teacher is (Gray & DiLoreto, 2016). The main goal of any curriculum is for students to graduate with satisfaction. When students are satisfied with a course, enrolment increases. Thus, student satisfaction is paramount. Educators may use both direct performance indicators (such as tests, projects, and presentations) and indirect performance measures (such as students' satisfaction with the quality of the course) to assess a curriculum's efficiency and effectiveness (Tessema, Ready, & Yu, 2012). On the importance of student satisfaction, Dhaqane and Afrah (2016, p. 59) made this statement:

> collecting and analysing student satisfaction data helps schools make sure their programmes meet the needs of a changing job market.

An evaluation of effectiveness metrics can be used to improve the curriculum at all levels– college, department, and programme. Hassani and Aghdasi (2014) found through their research that pursuing satisfaction rather than a formal academic degree is the best way to measure academic success. That is why teachers need to put student satisfaction as the foremost thing to do in any curriculum design–formal, informal and non-formal settings (Ezzat et al., 2009, as cited by Dhaqane and Afrah, 2016).

MOOC’s success is considered to the extent of student satisfaction (Hew et al., 2020; Rabin et al.,2019). Researchers at the Online Learning Consortium (OLC, previously Sloan Consortium) considered students' satisfaction with online learning in higher education essential in measuring online courses' quality (Dziuban et al.,2004).

When a person's wants, needs and expectations are met, that person will feel satisfied. When people talk about satisfaction, they mean a choice that makes someone satisfied (Rad & Yarmohammadian, 2006). A person's satisfaction or dissatisfaction is when he or she compares what actually happened to what was expected to happen (Kotler & Keller, 2012).

Students are more likely to stay in school if they are satisfied with the education system and the services they receive (Navarro et al., 2005). Students' perceptions of the utility of a particular learning system, such as a MOOC, may be influenced by their interactions with the system's instructional materials and customer service. This kind of interaction must be determined to improve future performance and service quality. Students' satisfaction is temporary and based on their feelings about their education, services and facilities (Weerasinghe & Fernando, 2017). The study only collects information at the beginning and end of the course. The level of satisfaction of college students is an important quality indicator that can be used to improve their education. Students’ satisfaction has become an important measure of the quality of education. It is usually used to improve the learning environment, especially regarding teachers and coursework. When students like what they are learning, it is a good sign that they are learning something (DeShields et al., 2005). On the other hand, what students want to get out of each course is concrete and measurable (Johnson et al., 2014).

How much students like and learn from MOOCs is a measure of how satisfied they are with them (Alraimi et al., 2015). That satisfaction results from how they think about the chance to learn (Rabin et al., 2019). Students' personal experiences determine whether or not they do well in school. Students’ satisfaction is linked to how well they do in school. Rabin et al. (2019) say that a different way to measure the effectiveness of a MOOC is to look at how satisfied the learners are. Learner satisfaction is important because it can affect how much they want to study on their own, which is a key factor in how well they do in school. By telling their friends about the MOOC Provider, satisfied students can help the business grow (Hew et al., 2020).

Moreover, just like satisfied blended MOOC learners want to tell their friends about it, they will use it whenever possible. People have said that researchers should not judge the success of MOOCs with traditional metrics like dropout rates (Rabin et al., 2019). On the other hand, metrics that focus more on the student's point of view, like learner satisfaction, are better (Rabin et al., 2019). Most schools want their students to be satisfied with their education, so asking those who have taken a blended MOOC about their experiences makes sense. This part of the study gives blended MOOC students enough support.

As many factors exist for any single issue that concerns students, so is for students' satisfaction. Different research studies arrived at various factors that influence students' satisfaction. The following paragraphs will be dedicated to listing some of these factors. Allen et al. (2003) observed different factors influencing learners' satisfaction: their digital literacy levels, appropriate academic guidance, the course learning design engagements–social and professional and the learner support system. Garnjost and Lawter (2019) mentioned high-quality instruction, professor-student connections and other factors affecting student satisfaction (Johnson et al., 2014).

Studies have found that MOOC learners' satisfaction depends on the following factors: Five elements predict learner satisfaction: 1) learner demographics, 2) learner motivation, 3) MOOC ease and usefulness, 4) learner disposition (e.g., responsibility for personal learning, goal-setting abilities), and 5) perceived MOOC design features that may predict learner satisfaction (Hew et al., 2020). Sun and colleagues measured student satisfaction across six dimensions: students, faculty, curriculum, infrastructure, and administration (Sun et al., 2008). Sun et al. also identified computer fear, teacher attitude toward the learning environment, course flexibility, course quality, perceived utility, perceived simplicity of use, and diversity in evaluations as critical factors in student pleasure (2008). Shrader et al. (2016) examined 2012–2015 research to identify MOOC learner satisfaction factors. These were pedagogy, content, assessment, usability, technology, learner support, interaction and collaboration. These make massive open online course participants happier and more inclined to learn (Shrader et al.,2016). Bangert found that student-instructor engagement and communication, time-on-task, active and engaged learning, and peer support predicted online student satisfaction (2006). From this brief literature review, students' satisfaction is complicated and many factors contribute to their overall satisfaction. Stakeholders within the education sector-administrators, teachers, parents/ guardians and learners- must explore these factors to boost students' satisfaction. User satisfaction is the most important factor in determining how well an information system works (IS). The level of satisfaction of a given IS's current users is linked to the likelihood that it will be used in the future. For learners to sustain and continuously use blended MOOCs, their satisfaction must be paramount.

Many authors have verified this assertion (Alraimi et al., 2015; Chiu et al., 2005; Lee, 2010; Lin et al., 2005). Students' decisions to keep using MOOCs were primarily based on how satisfied they were with their courses (Joo et al., 2018). In general, if students have a good experience with a MOOC, they are more likely to use it again. This claim is what a study on K-MOOC found. Again, Joo et al. (2018) made these observations:

a) How easy they think MOOCs are to use and how useful they think they have a positive effect on their overall satisfaction.
b) How satisfied they are with MOOCs indirectly affects their likelihood of using them.

Khechine and Lakhal (2018) found that the user's attitude, prior experience, expected outcomes and perceived value were affected by the enjoyment of using webinars for education. Again, Lee et al. (2015) asserted that attitude directly and positively influenced satisfaction. Regardless of the frequency of use and difficulty operating technology, those with a positive attitude about it will be satisfied with its use. Satisfaction might vary according to the variation in user behaviour (Dhaqane & Afrah, 2016; Martirosyan et al., 2014; Valentine, 2003).

Prior studies, such as the research conducted by Hew et al. (2020) and Rabin et al. (2019), have provided insights into the diverse aspects that impact student satisfaction in MOOCs. Nevertheless, a significant disparity exists in comprehending these dynamics in blended MOOC environments. This study seeks to address this disparity by investigating the impact of integrating online and conventional learning components in blended MOOCs on student satisfaction, particularly emphasising the distinctive attributes of University X. The findings of this research are anticipated to have substantial practical consequences for the development and execution of blended MOOCs. Educators and administrators can make well-informed decisions to maximise learning experiences by deepening our comprehension of student satisfaction in these courses. This study enhances the current knowledge by utilising and expanding pre-existing frameworks in the relatively uncharted domain of blended MOOCs.

2.13.2 Student Performance

For a protracted period, academic scholars have paid close attention to how engaged students are and what happens as a result, including how well they do in school. Engagement in learning has been known for a long time to be a key factor in how well students perform academically. Academic performance is multi-dimensional. Academic performance refers to a student's proficiency in schoolwork as measured by their grade point average or their progress toward the learning objectives established by their teachers over a given time frame (Narad & Abdulla, 2016). Students' academic performance is how they do on syllabi, assignments, and exams (Cambridge University Reporter, 2003, as cited by Kumar et al., 2021).

Finding out what students have done (performances) and how well they have done (performances) is a good indicator of their level of engagement in the learning process (Rajabalee et al., 2020). Performance is the performance obtained from the outcomes of learning activities. Many institutions rely on students' final grades or GPA regarding university academic performance evaluations. This study examines perceived performance as a function of the final grade within the blended MOOC. The final grade is based on the course structure, continuous assessment marks from exercises and quizzes, and the end-of-semester examination result. Using grades to measure academic performance can be inconsistent and unreliable as a measure of actual learning in a course (Templeman, 2020). Several alternatives are available to make course grades more comparable. Several alternative methods that have proven effective in educational environments include: 1) live scoring, which entails providing immediate feedback either verbally or in written form; 2) reflection narratives and self-assessments; 3) digital portfolios; 4) non-points-based rubrics; and 5) standards-based numerical reporting (Thomsen, 2013). When you look at how well students do on tests, you can tell how well they have learned what they have been taught in class (Dhaqane and Afrah, 2016). E-learning has received much attention because of its potential to cut costs and save time while enhancing education and making it more available (Zare et al., 2014). Strang (2017) discovered that online self-assessment quizzes help students learn and remain engaged, resulting in higher grades. Like any instructional delivery mode, predicting learners' performance from active participation in learning activities such as discussion forum posts and completed assignments within a blended MOOC environment is practically possible.

Many scholars have well researched and echoed student performance concerning e-learning. Nonetheless, the pressing matter is whether blended MOOC enhanced their academic performance irrespective of whether students accepted or rejected its use.

Regarding satisfaction and performance, Bean and Bradley (1986) arrived at the following conclusion:

- whether student satisfaction improves students' performance, as indicated by grade point average, or whether students' performance improves students' satisfaction is an interesting and important issue.
- Student satisfaction was found to be more influential when comparing the effects of student satisfaction and student performance. In other words, the effect of students' level of satisfaction on their grades was more significant than the effect of their grades on their level of satisfaction.

Student performance in MOOCs is measured using strategies, which are mainly distributed into automatic examinations (which are typically comprised of objective tests), peer assessments (in which students review the work of one another), and self-assessments (students appraise their personal work) (Bonafini et al., 2017). Grades demonstrate how well students learned and implemented the subject's learning outcomes (Fisher et al., 2021). Several studies show that blended learning improves student performance (Means et al., 2010

Student perceived performance, a crucial element of educational outcomes, has received significant attention from academic experts. Nevertheless, the scope of this discussion is limited to the context of blended MOOCs at University X, examining how this educational structure impacts students' view of their perceived academic accomplishments. Although the current body of literature offers a comprehensive grasp of perceived performance in many educational settings, there needs to be more knowledge regarding this issue, specifically in the blended MOOC environment. This study aims to close this divide by investigating the impact of incorporating blended MOOCs on students reported academic perceived performance at University X. The findings obtained from this research have substantial practical ramifications for the design and execution of blended MOOCs. Comprehending how students view their performance in this situation is essential for educators to enhance learning experiences and achieve desired results. This study expands upon current frameworks of perceived performance within the blended MOOC environment, thereby generating novel insights in this developing educational domain.

2.14 Summary

Chapter 2 examines how MOOCs affect student engagement and learning. An introduction sets the ground for an in-depth look at electronic learning, blended learning, and University X's e-learning landscape. It then examines MOOCs from a pedagogical and technological perspective. MOOC pedagogy is thoroughly examined, including learner-centeredness, curriculum structure, assessments, duration, content, textbooks, pedagogical tactics, discussion forums, live chat, and email communication. The chapter also discusses MOOC technology, such as learning management systems, platforms, and Web 2.0. Chapter 2 emphasises blended MOOCs, which combine online and face-to-face learning. The need for more research in this area opens the door to talks on blended MOOCs and learning. The chapter spends much time on MOOC student engagement, including its causes and effects on learning. The conversation then turns to learning outcomes, specifically student satisfaction and performance. Chapter 3 will discuss the adoption and use of technology and community of inquiry models, the two major models, which are the basis of the conceptual framework.

CHAPTER 3: THE ADOPTION AND USE OF TECHNOLOGY AND COMMUNITY OF INQUIRY

3.1 Introduction

Technology acceptance and use models are briefly highlighted in section 3.2. Section 3.3 provides a thorough background study of UTAUT. The reasons for using UTAUT for the study are discussed in 3.4. The need for research in technology adoption and use is highlighted in section 3.5. Section 3.6 briefly mentioned three online learning models. Section 3.7 introduces the Community of Inquiry (CoI) model, and Sections 3.7.1 and 3.7.2 examine the original and amended CoI frameworks, respectively, highlighting their importance in the study. Section 3.8 examines CoI in blended MOOCs. Section 3.9 examines educational experience with student engagement and CoI, highlighted in Section 3.10. Section 4.1 introduces online learning frameworks and their effects on student participation in blended MOOCs.

3.2 Technology Acceptance and Use Models

Just like any other information technology or information system implementation, failures exist in e-learning undertaking negating the effects of its perceived benefits (Regmi & Jones, 2020; Sun et al., 2008). Users' resistance to accepting and using such systems is one reason students' acceptance and use of any e-learning are crucial to its successful implementation. Acceptance of EdTech is why instructional and educational technologists and managers' survey end-users, such as staff's and students' e-learning readiness and experience. Such a venture aims to understand the factors affecting their acceptance of the systems to enhance their positive experience and achieve academic goals.

Due to the high cost of buying and running technology, research is done to discover how it can be accepted and used for what was intended. When trying to run a good e-learning programme, many factors come into play, such as human, organisational, social, technical, behavioural and cultural factors (Tarhini et al., 2015; Parsazadeh et al., 2013). Thus, there is a need to develop better ways to create, analyse, and predict how people will use new technologies. Technology acceptance is when users are willing to accept, adapt, adopt and use technology. People's acceptance of technology can be judged by whether or not they use it for its intended purposes. Technology adoption is a function of users' interest in using technology to improve their job performance and education, improving teaching and learning. Thus, technology adoption is a function of users' engagement in technology and influences its success. Whether a new technology is successful depends on how well many people use it.

Studying how technology can be used is a psychological outcome variable by which people decide whether or not a piece of technology will be used (Tamilmani et al., 2017). So, the value and usefulness of technology and how it is used depends on how many people use it. A technology that is not used has no value or usefulness. Therefore, technology has no value on its own unless people adopt and use it well (Oye et al., 2012). Many aspects of technology adoption have been investigated, from individual user characteristics like cognitive style to one's world views and how they affect user behaviour (Samaradiwakara & Gunawardena, 2014). One of the studies on technology acceptance and use objectives is to investigate what promotes and prevents the acceptance and use of technologies (Kripanont, 2007, as cited in Alshehri et al., 2012) to explain and predict their future use. Thus, technology adoption theories explain how people accept new technologies and how they plan to use them. The goal of technology acceptance models and theories is to specify a route of technology adoption from external influences through attitudes, intentions, adoption and actual use. The term "technology adoption and use" refers to the process by which individuals embrace new forms of technology.

As a result, one objective of this study is to determine how people will use blended MOOCs using design, evaluation and prediction techniques. User behaviour factors towards the acceptance, adoption, adaptation and usage of information systems and information technologies such as e-learning and MOOC have been explored in depth through theories and models (Taherdoost, 2018).

These theories and models illuminate the acceptability and usefulness of IT/IS at the individual and organisational levels (Martins et al., 2014). Organisations often use the Innovation Diffusion Theory (IDT) and the Technology Organisation Environment (TOE) framework (Alghatrifi & Khalid, 2019; Martins et al., 2014) to facilitate the spread of new ideas and practices throughout the company. Theory of Reasoned Action (TRA), Planned Behaviour (TPB), Decomposed Theory of Planned Behaviour, (DTPB), Technology Acceptance Model, (TAM), Unified Theory of Acceptance and Use of Technology, (UTAUT), Social Cognitive Theory, Model of PC Utilization (MPCU) are most influential theoretical models at the individual level in the literature (Gangwal & Bansal, 2016). In an effort to capture the dynamic between user beliefs, attitudes, and intentions, these theoretical models developed at the individual level serve as the starting point for such investigation. User intent to use IT/IS across contexts is grounded in TRA, TPB, and TAM (Martins et al., 2014).

3.2.1 Unified Theory of Acceptance and Use of Technology

The short form of the Unified Theory of Acceptance and Use of Technology is UTAUT. There are two versions of it, namely UTAUT and UTAUT 2. In the latest article on the framework, Venkatesh, a principal author of both UTAUT and UTAUT 2 and colleagues, said:

> UTAUT accounted for 77% of the variation in tech-use intentions and 52% in actual tech-use rates. However, another study found that UTAUT2 accounted for 52% of the variance in consumers' actual technology use and 74% in consumers' behavioural intentions to utilise technology (Venkatesh et al., 2016).

3.2.2 UTAUT

Venkatesh et al. (2003) looked at eight popular models and came up with UTAUT, displayed in **Error! Reference source not found.** UTAUT was initially conceived as an explanation for adopting and utilising technology in the workplace (Venkatesh et al., 2012). There are eight models containing thirty-two constructs that Venkatesh et al. (2003) studied. They looked at these eight models because they thought they could help them figure out how people use their computers. How does the UTAUT theory work? The authors say that people's willingness to use new technologies is affected by what they expect in terms of performance (performance expectancy), effort (effort expectancy), facilitation and social influence. The most important things that affect how users act are their intention and the conditions that make it easy for them to act or use the technologies. The independent factors are the expectation of performance, the expectation of effort, the influence of others and the enabling circumstances. Thus, behavioural intention acts as a bridge between the user's actions and the results. UTAUT propounds four things affect these dimensions of behavioural intentions and technology use. They include gender differences, age, experience, and willingness to help (whether or not individuals use technologies autonomously). This new model, which is better than all eight previous models and extensions, explained 70% of the differences in what users meant to do. UTAUT uses fewer factors (four main factors) for a higher prediction, making it more parsimonious than most of the eight models. Figure 3-1 shows the UTAUT model with its factors.

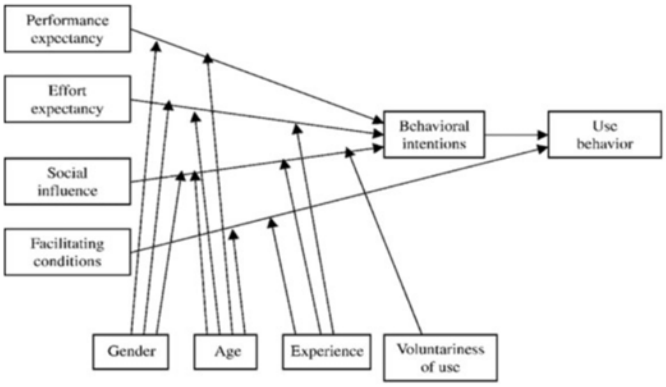

Figure 3-1.The UTAUT Model

Source. Venkatesh et al. (2003).

From the eight models, seven factors seemed to be good direct predictors of intention or use: 1) attitude toward the use of technology, 2) self-efficacy, 3) anxiety, 4) expectations of performance, 5) expectations of effort, 6) social impact, and 7) facilitating conditions. Nevertheless, the first three were ruled out as direct predictors of intention for UTAUT (Venkatesh et al., 2003). Most of the eight models use more factors to make a prediction; however, UTAUT only uses fewer factors (four main factors) to make a better prediction. This assertion makes UTAUT more parsimonious than most of the eight models. The following paragraphs briefly summarise each of the UTAUT model's four extrinsic cognitive drivers.

3.2.2.1 Performance Expectancy

Performance expectancy measures how much people think, using the system will help them do their jobs better. Intrinsic motivation (MM), job fit (MPCU), perceived usefulness (TAM/TAM2 and C-TAM-TPB), relative advantage (IDT), and outcome expectations (SCT) are all related constructs of performance expectancy that come from the models assigned to them.

Again, usefulness, intrinsic motivation, work fit, relative advantage and expectations of results are all terms that go together. Venkatesh et al. (2003, pp.447-450) made the following observations.

- Gender and age offer a moderating influence on the relationship between performance expectation and intention.

- Men are very task-oriented; as a result, males place a high value on task-oriented performance expectations.
- Gender and age variations arise in situations of technology adoption together; gender differences without regard for age might be inaccurate.

3.2.2.2 Effort Expectancy

Effort expectancy is a term for how easy it is to use a system. The idea of effort expectancy is covered by three of the eight existing models: perceived ease of use (TAM/TAM2), perceived complexity (MPCU) and perceived ease of use (TAM/TAM2) (IDT). Venkatesh et al. (2003, p.450) came to the following conclusions.

- Each model's effort expectancy construct is significant for voluntary or mandatory usage scenarios.
- Effort expectancy is particularly relevant during the early phases of a new behaviour when process concerns may be impediments to overcome and are eventually superseded by instrumentality concerns.
- Women place a higher value on effort expectations than men do.
- For women and older users, effort expectations will be a more significant predictor of intentions.
- Women, particularly older ones and those with little experience with the system, will be most affected by effort expectations.

3.2.2.3 Social Influence

When people talk about "social influence", they mean how much they think that influential people think they should use the new system. The subjective norm in TRA, TAM2, TPB/DTPB, and C-TAM-TPB, social factors in MPCU, image in IDT and social norms represent social influence. Social influence is negligible, while use is voluntary, but it becomes important when mandated. Venkatesh et al. (2003) made the following observations:

- In a mandatory situation, the impact of social influence is due to regulatory compliance. In contrast, it operates within voluntary circumstances through changing views of the technology (i.e., internalisation and identification). Social influence affects how people accept new technologies in three ways: compliance, internalisation, and identification.

- The terms "internalisation" and "identification" describe how an individual's worldview is shifted in reaction to the prospect of an uptick in their social standing.
- The individual's intention shifts from resisting to complying with the social pressure, thanks to the compliance mechanism.
- Women are more open to the ideas of others and place greater weight on the opinions of their peers when deciding whether or not to adopt new technology. This effect fades with time and practise.

3.2.2.4 Facilitating Conditions

Facilitating conditions are how much a person thinks an organisational, technological and technical infrastructure is in place to help them use an application or information technology/system. In the eight models, facilitating conditions encompass these distinct concepts: compatibility (IDT), and facilitating conditions (MPCU), perceived behavioural control (TPB/DTPB, C-TAM-TPB). Venkatesh et al. (2003, pp.453-455) made the following observations.

- Facilitating conditions include elements of the technological and organisational environment aimed to remove barriers to use.
- Also, the effort expectancy construct is a big part of how problems with the support infrastructure are captured.
- Facilitating conditions are predicted to rise with experience as technology users find many sources for aid and assistance throughout the organisation, lowering challenges to continuous usage.
- In light of the growing cognitive and physical demands imposed by modern ICT use, and challenges related to ageing, older people attach increased importance to receiving technical support on the job.
- Thus, when controlled by experience and age, facilitating conditions will significantly influence user behaviour.

3.2.2.5 Behavioural intention

Behavioural intention is a term taken from the theory of planned behaviour that refers to the perceived likelihood that an individual will partake in the desired behaviour. It is a common factor in all theories of technological acceptance. Users should be prepared to engage in a given behaviour before engaging. It concerns how an individual has pre-set plans to conduct or refrain from performing some defined future behaviour. It describes the process of determining the strength of a user's intent to carry out an action plan to use a given technology. The desire of a person to use a certain technology directly affects how they actually use it. How a system is used depends on what the user wants to do with it. When it comes to a person's willingness to do something, that willingness is often seen as a direct cause of the behaviour. As a result, people's computing habits will significantly improve thanks to the power of behavioural intention. Computer self-efficacy, computer anxiety, and attitude towards technology use were not substantially associated with behavioural intention, as Venkatesh et al. (2003, p. 4) found. This is because effort expectancy incorporated these effects. Figure 3-2 shows that Venkatesh et al. (2012) made and tested a new structure called UTAUT2. It brings together new ways of thinking about consumer behaviour, like hedonic motivation, price value and habits. UTAUT 2 was created to investigate how technology is embraced and applied in the context of mobile Internet users. Hedonic motivation, price value, and habit are the three constructs that the model integrates into UTAUT to accomplish the desired outcome. Age, gender, and experience were three more moderators who were in charge of handling individual variances. However, one of the four moderators in UTAUT, voluntariness, was dropped.

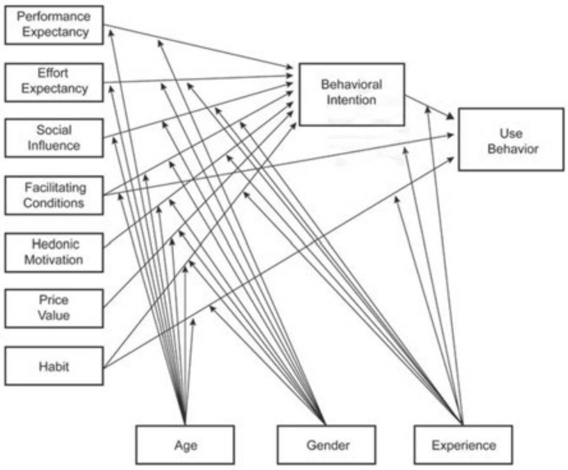

Figure 3-2.The UTAUT 2 Model.

Note. The UTAUT 2 Model (Venkatesh et al., 2012).

3.2.3 UTAUT 2

The following paragraphs summarise the three new factors in the UTAUT 2 model.

3.2.3.1 Hedonic Motivation

People act in ways that lead to rewards or away from punishments and look for pleasure and avoid pain. A person's sense of pleasure and pain can make them want to move toward a goal or away from a threat. Hedonic motivation is based on people's desire to get pleasure and avoid pain (Higgins, 2006). A person's desire to do things that make the good experience better or make the bad experience worse can make positive and negative experiences better or worse, respectively (Kaczmarek & Mickiewicz, 2017). It is the willingness to do things that make the positive experience (good or pleasant) better and the negative experience (bad or unpleasant) less bad (Kaczmarek & Mickiewicz, 2017). Thus, hedonic motivation is the feeling of fun or pleasure that comes from using technology (Brown & Venkatesh, 2005). Additionally, it has been discovered that how people embrace and use technology is significantly influenced by their need for pleasure. (Brown & Venkatesh, 2005; van der Heijden, 2004).

Because most technologies were made to be effective and efficient, hedonic motivation in the field of technology looks at the positive and fun parts of the classic definition. Hedonic motivation is thought of as a sense of pleasure (van der Heijden, 2004). The focus is on how much a person likes using technology or how much fun or pleasure they derive from it. Thus, hedonic motivation is the feeling of fun or pleasure that comes from using technology (Brown & Venkatesh, 2005). Also, people's desire for pleasure has been found to play a significant role in how they accept and use technology (Brown & Venkatesh, 2005; van der Heijden, 2004).

Regarding UTAUT 2, Venkatesh et al., 2012 made the following observations.

- Hedonic motivation is a significant factor in how people plan to act. It is more important than performance expectations in non-organisational situations.
- People of different genders, ages, and experience levels play a role in how hedonic motivation affects their behaviour.

Hedonic motivation can make people more likely to do what they want, which is valid for younger men with less technology experience.

3.2.3.2 Price Value

Price is what an individual pays for something or what the market thinks something is worth. Value is what an individual thinks the thing is worth or what they think it is worth. When someone buys something, they value it because of its value for hedonic and utilitarian reasons. This monetary worth placed on technology is the price value of technology. Venkatesh and his colleagues made UTAUT for business in view. However, Venkatesh and other colleagues worked on UTAUT 2 in a consumer setting powered by web and mobile computing. Thus, there is a big difference between the two settings regarding who pays for technology. Usually, people who buy technology have to pay for it themselves. However, people who use technology at work do not have to pay for it alone (Venkatesh et al., 2012). Organisations are responsible for providing, maintaining, and keeping their system alive. In this way, technology's cost and pricing structure may impact how people use it. That is why Venkatesh and his colleagues included price value as a predictor of how likely people are to use technology in UTAUT 2 (Venkatesh et al., 2012). The pricing value is how consumers weigh the perceived benefits of the apps against how much they cost (Dodds et al.,1991, cited in Venkatesh et al., 2012). According to Venkatesh et al. (2012, p. 161), the authors state the following. In instances where the advantages of technology surpass its associated costs, the influence of price value on behaviour tends to be mitigated by factors such as age and gender.

- When the benefits of the technology outweigh the related costs, the price-value proposition is deemed favourable.

- Age and gender have an impact on how price value influences conduct intention.
- It is probable that men assign a higher value to technologies than women when evaluating the same technologies. Furthermore, it is observed that older women exhibit a greater level of attentiveness towards the monetary value associated with various products and services.

3.2.3.3 Habit

Technology acceptance research that predicts how people will use technology in future focuses on either conscious intentions or non-conscious, automatic predictors, such as a habit. It was observed that other non-planning or unconscious aspects internal to the individual, such as habit, might also influence technology acceptance. While Kim et al. (2005) considers automaticity synonymous with habit, Limayem et al. (2007) define habits as the degree to which previously taught behaviours are performed without conscious thought. According to Limayem et al. (2007), habits comprise past behaviour, how often they happen, quick reactions, individual experiences and how each person reacts to them. There are two methods to determine habit, which differ from one another. First, habit is considered previous behaviour (Kim et al., 2005). Second, habit is measured by how automatic an individual thinks the behaviour is (Limayem et al., 2007). It is believed that individuals' continuous usage of technology can be predicted using their habits about its use over time is essentially a function of habit rather than conscious intentions. Therefore, encouraging the users' acceptance of new technology based on habits can be essential to the success of new systems.

Habit as automaticity is conceptualised in literature from two different perspectives: behaviourism and cognitive-motivational. Behaviourism looks at habit from a stimulus-response point of view that mostly ignores psychological states and mental processes. According to Sheeran et al. (2005), behaviourism posits that the frequency of engaging in a particular behaviour directly influences the strength of the corresponding habit. In contrast, according to the cognitive-motivational perspective, a habit is a process wherein goals are mentally linked with the actions that facilitate their attainment (Verplanken, 2006). Per the findings of Polites and Karahanna (2013), goals in this context pertain to the desired or anticipated outcomes or end states, as well as the anticipated and desired consequences that guide the performance of the behaviour.

There are a lot of different opinions about how long people should keep using technology. Some people think that technology use habits can be formed over time through much practice. As people keep using technology for their daily tasks for a long time, they may reach a point where this habitual behaviour happens without them even realising it (Bargh, 1990; Polites & Karahanna, 2013). Although Tamilmani et al. (2018) contend that relying solely on past experiences should not be used to determine habitual behaviour, there are differing viewpoints. They say that although having prior experience with technology is required to create a habit, prior experience alone is not a sufficient requirement for habit formation. Again, Tamilmani et al. (2018) recommended that habits should not be used in mandatory settings, such as students' acceptance of LMS, due to the involvement of compulsion and social pressure. In such a situation, habit is driven by extrinsic rather than intrinsic motivation. The construct habit was the most critical new factor in UTAUT 2. It challenged the idea that a person's behavioural intention was the only thing that led them to use technology. UTAUT2 model: habit is a function of behavioural intention and user behaviour in the UTAUT2 model.

3.2.4 Reasons for using UTAUT in the study.

TAM and UTAUT are two of the most often-used acceptance and use theories (Shachak et al., 2019). TAM and UTAUT predict how someone plans to use technology and how they use it. In Information Systems Research, TAM and UTAUT have been used extensively. It also notes that TAM's simplicity has been criticised. However, this makes it an excellent way to test how well new technologies are accepted in a "quick and dirty way". This argument makes TAM less helpful in explaining things and does not tell us much about how people use it (Shachak et al., 2019). Other TAM's criticism are its poor heuristics, weak explanatory and predictive capacity, triviality, and lack of practical value (Chuttur, 2009). Again, a full review of the research published between 2011 and 2016 on why people use MOOCs as EdTech found 11 papers that focused on how people accept new technologies. Six of these papers used TAM, two used UTAUT, one used TAM3, and one paper each used the theory of planned behaviour (TPB) plus self-determination theory (SDT) and the information systems continuance expectation-confirmation model (Hakami et al., 2017). Also, Azami and Ibrahim (2018) found that ten of the 16 articles about accepting MOOCs used TAM and six used UTAUT.

Based on what has been said so far, the TAM and UTAUT models are the ones most often used to study how users accept MOOCs. Mulik et al. (2016) also found that, with a few exceptions, all TAM and UTAUT constructs affect MOOC acceptance and the intention to use them. Since TAMs (TAM, TAM2, and TAM3) and UTAUTs (UTAUT and UTAUT2) are the two most common user acceptance models (Venkatesh et al., 2003), either one could be used. UTAUT, on the other hand, was chosen for this study because:

- Venkatesh used TAM when constructing UTAUT; thus, all of the constructs from TAM can be found in UTAUT, and therefore it makes sense to use UTAUT rather than TAM.
- UTAUT is better than TAM and can make better behavioural intention and usage predictions than TAM.
- Google Scholar estimates there are 26,029 citations for TAMs (which include TAM, TAM2, and TAM3) and 29,954 for UTAUTs (which include UTAUT and UTAUT 2). The implication is that UTAUT is more popular than TAM.
- UTAUT is the most in-depth model in the field of research on IS/IT adoption (Tamilmani et al., 2017).

UTAUT is the most popular model for analysing how people use technology, and it does a better job than other models; UTAUT can account for 70% of the variance in Behavioural Intention to Use (BI) and 50% of the variance in actual use (Venkatesh et al., 2003).

Most UCC students use mobile computing (laptops, tablets and smartphones) for academic and non-academic activities on campus and at home (Edumadze, 2019). Again, mobile learning is their preferred digital learning environment (Edumadze et al., 2019). Venkataraman and Ramasamy (2018) suggested that UTAUT is the best possible model for mobile learning. Most UCC students learned about MOOCs for the first time when they signed up for and took part in Information Technology Skills 101 (ITS101), a blended MOOC course level 100. Thus, the survey respondents are using blended MOOCs at the beginning, even though it is not required at UCC to use them as a way to teach. Venkatesh et al. (2016) suggested that UTAUT2 could be used in the beginning phase of the target technology (e.g., adoption, initial use). There have been different reports about how the MOOC model is being adopted and used. In some cases, researchers like Ren (2019) have argue that teachers, students and institutional policies make it hard for MOOCs to be accepted as an innovative and alternative way to teach. Also, research and practice have focused a lot on how innovations are accepted and used in higher education institutions like universities (Nguyen et al., 2014).

Finally, even if UCC students are skilled at utilising mobile devices, the particular circumstances of blended MOOCs offer special factors and difficulties that call for a different study on their adoption of new technologies. This study will add to the corpus of knowledge in educational technology by offering greater insights into the variables impacting the successful integration of blended MOOCs into higher education.

3.2.5 Technology acceptance models used for MOOCs research

People cannot benefit from technology unless they use it, making this part of the study very important. Nevertheless, why do people accept to use technology or not? Then, acceptance of MOOCs talks about why people accept MOOCs or not. After looking at 42 related papers about why people sign up for MOOCs, the conclusion was that there is not much research on how people use MOOCs and what makes them useful (Azami & Ibrahim, 2018; Hakami et al., 2017). After a thorough literature review on MOOCs by Guptaa (2019), the following conclusions were made:

- Few studies have examined how students in developing countries respond to MOOCs and their variations, such as blended MOOCs.
- Sub-Saharan Africa or Ghana was not the research focus in any of the papers mentioned. This dearth of studies on students' adoption of MOOC/blended MOOC is one of the gaps this study tries to fill.

Furthermore, researchers found that only a few papers use the technology acceptance theories (Hakami et al.,2 017). So far, what has been said makes it hard to know how people in this region use them (Veletsianos & Shepherdson, 2016).

Knowing what drives people to use MOOCs is essential, so teachers, universities, and providers can determine how many people might use them. For educators in the developing world, understanding these determinants of the adoption of MOOCs will likely help them overcome possible barriers and use them more. Adopting technologies like MOOCs will ultimately help bridge the digital divide (Liyanagunawardena et al., 2013). Exploring factors influencing the adoption of MOOCs deals with identifying its drivers and barriers, *i.e.*, figuring out what makes people want to take or not take MOOCs. Different variables can be drivers and barriers, like the technology's features, the user's characteristics and social and environmental factors. Most research on technological adoption traditionally focused more on drivers than barriers. An integrated view fully explains the factors affecting people signing up for blended MOOCs.

3.2.6 The need for research in the user acceptance model for blended MOOC

As indicated in the preceding section, many factors come into play in successful blended MOOC implementation: behavioural, individual, organisational, social and technological (Tarhini et al., 2015). Again, cultural, political and situational differences explain varying MOOC acceptance and usage degrees. All these factors should be investigated locally to emphasise or highlight those factors promoting blended MOOC. When these are done, positive experiences and successful use of blended MOOCs could be attained. Again, concerning MOOCs/blended MOOCs, countries in sub-Saharan Africa lack reliable ICT infrastructure and have inadequate and lack quality learning resources (Oyo & Kalema, 2014). Most learners are digitally challenged in access, ownership, and digital skills, with very few online learning experiences (Veletsianos & Shepherdson, 2016). However, these aforementioned present opportunities and challenges in using MOOCs, making the drivers and barriers influencing MOOC adoption and experience between developed and developing countries different (Oyo & Kalema, 2014). There is still a need to investigate factors specific to MOOCs and their blended form, which may drive students' motivation to learn (Guptaaa, 2019). In response to these factors, Numerous theoretical frameworks have been put forth to examine and delve into the factors influencing individuals' attitudes and behaviours about adopting, adapting, and utilising educational technology (EdTech) to attain educational objectives. Additionally, various approaches have been suggested to assess and evaluate students' online learning experiences.

There have been calls for investigations of blended MOOCs in different university settings (Caulfield et al.,2013). Much has been written about online community behaviour in MOOCs, but little information exists about the blended MOOC community. Thus, research is needed as online communities' current design might not adequately serve the needs of blended MOOC for full-time students (Caulfield et al.,2013). More so, most studies on blended MOOCs — their prospects and problems — come from the origin of the MOOC movement in North America (the United States and Canada) and Europe. Other continents, sub-regions and countries with different cultural environments, educational policies, and regulatory frameworks from the Western world need their specific context on MOOCs examined for their global outlook. This study will provide Ghana's perspective on MOOCs to understand better significant differences in benefits and challenges across the globe in using and reusing MOOCs with the local content as blended MOOCs.

After an analysis of forty-two related papers on the motivation for enrolling in MOOCs, the conclusion was that the volume of research on MOOC adoption and the variables affecting their use in the developing world is minimal (Hakami et al., 2017) with a similar conclusion arrived at by Azami and Ibrahim (2018). Again, studies highlighting African perspectives are still understudied despite MOOCs' potential to help learners from the global south taste online education and innovative research of the global north.

Besides, authors have written much about online community behaviour in MOOCs. However, little information exists on blended MOOC communities (Caulfield et al., 2013). Although technology is valueless unless used (Oye et al., 2012), how students accept and use blended MOOCs has salient theoretical and practical implications, making this aspect of the research very necessary. Understanding the factors that may encourage blended MOOCs' success or failure within developing countries is vital to regularising such an instructional delivery strategy. The reason is that blended MOOC is uncharted territory in developing countries with much to be learned, especially regarding students' acceptance and experience of using them.

While user acceptance models have seen widespread adoption in more traditional forms of online education, their use in blended MOOCs is still in its infancy. As a result, more studies are required to determine whether or not they are helpful in the setting of blended MOOCs. There may be real-world applications for school administrators and policymakers from studies of user acceptance models in blended MOOCs. Policymakers may do more to promote the use of blended MOOCs by students if they better understand the elements that impact students' decisions to choose them. As a result, more studies into blended MOOCs and the application of technology acceptance models are required. Learners' motivations, expectations, and overall impressions of blended MOOCs can be better understood if researchers analyse the efficacy of user acceptance models in this context. To further the development of online education, this knowledge can assist MOOC providers and policymakers in creating effective policies and programmes that promote the adoption of blended MOOCs.

Finally, this study examines the use and perception of blended MOOCs offering credit-bearing options due to their diversity. Policymakers must understand how students use credit-bearing blended MOOCs to improve their adoption. These reforms could boost regional economic growth by boosting access to higher education and matching educational performances with labour market needs.

3.3 Online Learning models

Teachers, students, and administrators employ technology to create scholarly communication settings because communication is the heart of education (Epelboin, 2017). In this context, e-learning environments, learning management systems and other EdTech solutions are critical for successfully establishing, promoting, and maintaining communication with online learning communities (Rubin et al., 2013). Communication should occur between learners, learners and instructors and the learning community and its resources for learning. These modes of communication foster cooperation, collaboration, dialogue and community participation (Goodyear et al., 2004). As with its traditional face-to-face classroom counterpart, theory should regulate online education teaching and learning.

As no single learning theory reigns supreme in the general instructional delivery mode, no theory exists in online education. Community of inquiry (CoI) (Garrison et al.,1999), connectivism (Siemens 2004), and online collaborative learning (Harasim 2004), however, stand out as the commonly used frameworks for online education (Azar et al., 2021; Bates, 2015; Jabbar et al., 2021; Picciano, 2021; Quezada et al., 2020). Coincidentally, the originators are all Canadian based. This study concentrates on the community of inquiry and one of its variants, which includes the learning presence.

3.3.1 Community of Inquiry

As a social constructivist-collaborative paradigm, Garrison et al. initially suggested the CoI framework (1999). The Community of Inquiry (COI) model is a way of teaching and learning online that focuses on group work, analytical thinking, and shared knowledge. Students in a community of inquiry engage in collaborative learning through online conversations and other activities to better comprehend course content. It is an approach to education that uses the web and emphasises group work, analysis, and camaraderie. Within a community of inquiry, students collaborate through online conversations and various activities to investigate course content, exchange ideas, and cultivate a more profound comprehension of the subject matter. Garrison (2017) analyses the key elements necessary for a prosperous online higher education learning experience, drawing from Dewey's educational theory and social constructivism. Dewey based his philosophy of education on the values of inquiry and cooperation (Swan et al., 2009). Dewey thought that education should combine the needs of the individual with those of society and that personal growth depends on the community, teaching students how to be involved as active members of society. To reach this goal, education should be a process in which both students and teachers work together to create a supportive setting for learning involving inquiry, working together and sharing ideas within a community, which is vital for our sense of belonging and identity.

- He emphasised inquiry-based learning, encouraging students to think critically and solve problems. Inquiry is the process of asking questions, trying to find solutions, and looking into new ideas. In education, inquiry-based learning is a way for students to engage with course material and use critical thinking skills actively.
- Students learn best when they are actively involved in a) making sense of knowledge, b) taking responsibility for their learning, c) connecting meaningfully with the material and d) collaborating, cooperating and valuing the individual are essential to successful learning.

A community is a group with the same goals, hobbies or experiences. Education involves a group of students, teachers, and other stakeholders working together towards a shared goal. Collaborative learning is a way of teaching that encourages students to work together in groups to reach a shared goal. Cooperative learning is similar to collaborative learning but stresses each person's responsibility and the group's interdependence more. Concepts like community, collaborative or cooperative learning and students taking responsibility for their learning make students' engagement a pivotal factor in the success of this educational theory. Moore (2013) identified three main types of interaction in online education: learner-instructor, learner-learner and learner-content.

- Learner-instructor: This refers to the teacher's work to create the course's curriculum, organise information and activities, and help and support students to get them more interested and motivated in the course. It also looks at students' dealings with the teacher during the course.

- Learner-learner: This type of interaction is when students talk to each other in groups or in the learning community, with or without instructors. The goal here is for learners to learn from each other.
- Learner-content: The objective is to interact intellectually with learner-content in a way that helps the learner understand the subject and changes how the learner thinks to engage with content.

3.3.2 The original CoI

The CoI framework was originally built around three different ideas called "presences": cognitive presence (CP), social presence (SP) and teaching presence (TP) (Garrison, 2011). The way students interact with one another while taking an online course is called their "presence." Each node in the CoI model is a conversation happening over the internet. The CoI model is related to three kinds of interaction in an environment where computers are used to teach and learn. Swan (2006) concluded that three parts of the CoI model match Moore's three types of interaction (2013). Teaching presence is interacting with instructors, social presence is interacting with other participants, and cognitive presence is interacting with content.

From the CoI, the three presences (cognitive, social, and teaching) impact learners' inquiry-based learning experiences within a learning community. CoI is a "generic and cohesive structure for a transactional educational experience, with the primary goal of managing and monitoring the dynamic for collaborative thinking and learning" (Garrison, 2017, p. 24). Garrison et al. (2015) defined CoI as "a group of persons who collaborate on purposeful, critical dialogue and contemplation to develop personal meaning and confirm mutual understanding"(p.13). The CoI model is based on the idea that courses should be more like active learning communities where students and teachers can share their knowledge and points of view. CoI suggests that for students to make significant progress, they need to learn in an online setting in a way that is based on questioning and problem-solving. The CoI model has become one of the most popular online and blended learning models, with synchronous and asynchronous communication technology facilitating high levels of engagement between students and lecturers.

Vaughan and Garrison (2008) assert that CoI is founded on two fundamental notions for significantly higher education in an era powered by internet technologies- web 2.0 and social media: 'community' and 'inquiry'. The community recognises the social dimension of education, emphasising the need for interaction, collaboration, and conversation in knowledge construction (Arbaugh, 2007; Ranjan, 2020). The process of generating meaning through personal responsibility and choice is reflected in inquiry (Arbaugh, 2007). Again, Ranjan (2020) defined inquiry as how students develop meaning through their initiative and selection (Ranjan, 2020). Thus, two components of COI are cohesion and participatory community of learners. COI's mission is to "critically analyse, develop, produce, and validate new knowledge" to deliver meaningful educational experiences (Garrison & Vaughan, 2008, p. 9). From Bates (2015), CoI is more of a theory than a model, as it does not specify the activities or situations under which teachers must produce the three 'presences'. CoI is a term that refers to the process through which students learn through active engagement with questions or issues, aided by various interventions (Cleveland-Innes, 2019). Garrison et al. (1999) illustrated the relationship between the three elements with the Venn diagram depicted in Figure 3-3. Many subcategories have been made to show different parts of the existence of each component. The four stages of cognitive presence are triggered, explored, integrated and resolved. Teaching presence includes guiding a conversation and giving direct instructions. A person's social presence shows how well they can communicate, how openly they can communicate, and how well their community works together.

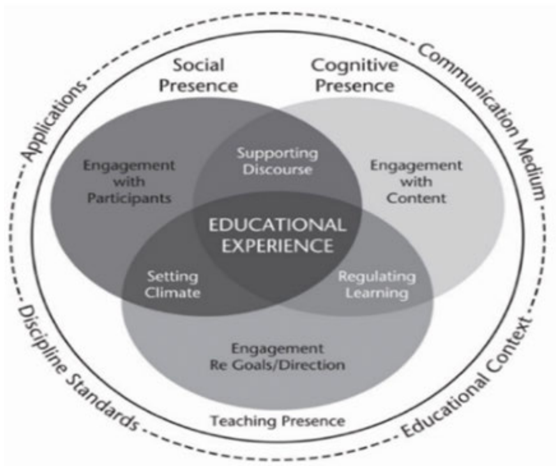

Figure 3-3.Elements of Col model.

Source. Garrison et al. (1999).

3.3.2.1 Cognitive presence

Cognitive presence (CP) is the extent to which a community of inquiry may build understanding through discussion (Garrison et al., 2000, p. 89). CP argues that any educational experience should foster critical thinking (Garrison et al., 1991). CP is a learner's capacity to generate knowledge through dialogue and reflection (Swan & Ice, 2010). However, learners in online learning settings require more than CP to be considered members of an inquiry community (Castellanos-Reyes, 2020). CP employs a practical inquiry model in which learning begins with experience, progresses through reflection and conceptualisation to action and returns to much more experience (Garrison et al., 1999). The Practical Inquiry Model, depicted in Figure 3-4, explains the inquiry process of generating meaning from experience, specifically in the CoI framework for an educational experience.

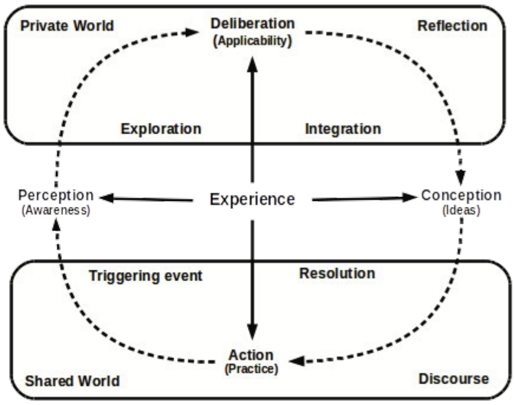

Figure 3-4.Practical Inquiry

Source. Garrison et al. (1999).

The initial stage involves a triggering event, during which an issue or problem is identified and delineated. The subsequent stage entails an examination of the issue at hand and acquiring accurate and pertinent information. During the third phase, individuals engage in the process of organising and comprehending the information at hand. Various solutions are conceived and subjected to rigorous debate. The selected solution is implemented and evaluated directly or by a third party during the final stage. If the provided answer is deemed inadequate, it may initiate subsequent inquiries.

3.3.2.2 Social presence

People in a community of inquiry's ability to express themselves socially and emotionally and present their real personality through their chosen medium is called social presence (SP) (Garrison et al., 1999). SP was used to foster connectivity and collaboration inside the online learning environment (Castellanos-Reyes, 2020). Researchers characterised SP as a learner's capacity to form emotional connections with peers and perceive their entire personality in an online learning environment (Garrison et al., 1999; Swan and Ice, 2010). Learners create collaboration channels to facilitate effective learning by leveraging the affordances of existing online learning technology (Garrison et al., 1999). Thus, SP distinguishes asynchronous online learning from content consumption (Castellanos-Reyes, 2020). SP improves CP when students and teachers work together to express emotions, communicate openly, and build community (Garrison et al., 1999). From Garrison et al. (1999), these actions build a social presence:

- Expressing emotions in education means being able and confident to convey learning-related feelings.
- Reciprocal and polite interactions describe open communication.
- Open communication includes explicitly displaying mutual knowledge and accepting others' thoughts, which is especially crucial online since smiles and eye contact may not be available.

Students who see themselves as a group are likelier to collaborate and engage in critical thinking. Students require the teacher's assistance in fostering critical thinking and teamwork in any formal educational context.

3.3.2.3 Teaching presence

In the formal, traditional education setting, creation and administration of the educational experience is the responsibility of a teacher, this is what teaching presence is about. The teacher-led design includes "the choice, arrangement, and main delivery of course material, along with the creation and implementation of learning activities and evaluations" (Garrison et al., 1999). The CoI framework defines teaching presence (TP) as the deliberate arrangement and guidance of cognitive and social activities to facilitate student learning. TP includes instructional management, understanding, and direct instruction. Instructional management includes planning curriculum, instructional methods, assessments, timelines, and resources (Garrison et al., 1999). Building understanding involves learners acquiring knowledge. This requires the teacher to engage with less active participants actively, recognise their contributions, reinforce them, steer the conversation, and facilitate an educational exchange (Garrison et al., 1999). Direct instruction delivers material and assesses student comprehension (Garrison et al., 2000). Conrad (2005) suggests that effective teachers foster community within their educational environments, whereas ineffective teachers fail. In other words, good teachers have an excellent educational experience, while bad teachers do not.

3.3.3 The revised CoI

Many authors have suggested extending the original three presences of the CoI framework. The new presence types proposed as additional presences are autonomy presence, learning presence, emotional presence, instructor's social presence and vicarious presence (Anderson, 2017; Kozan & Caskurlu, 2018). Including these presences is to refine the CoI framework, making it more robust and comprehensive (Kozan & Caskurlu, 2018) and thoroughly describing the educational experience (Anderson, 2017). Apart from the learning presence, none of these proposed additions has been widely adopted. The reasons that have been forwarded to maintain the three presences are:

- Anderson (2017), the three presences provide a parsimonious advantage.
- Kozan and Caskurlu (2018), the suggested presences can be incorporated into the model by expanding the scope of the three presences' definitions or the interrelationships between and among the three presences.

The inclusion of the learning presence has received mixed acceptance from two of the originators of the CoI framework, Garrison and Anderson. While Garrison rejects its inclusion, Anderson supports its inclusion. The reasons Anderson (2017) forwarded in support of the inclusion of the learning presence are 1) it brings on board the notions of self-directed learning, and 2) it transforms COI's "teaching model" into a "teaching and learning paradigm," expanding its application to transcend the confines of traditional schools and educational situations. Other reasons Anderson (2017) stated in his supporting argument for the inclusion of the learning presence in the CoI framework:

- The current CoI paradigm is only useful for building and defining an efficient teaching framework.

- It brings CoI closer to the principles of autonomous learning advocated by constructivist learning and heutagogical approaches to education.
- It expands the scope of the CoI from purely pedagogical to one that incorporates learning, making it applicable in settings beyond the classroom. It has potential for learning as demonstrated by the students.

Why Garrison(2017b) does not think the learning presence should be included in the CoI framework:

- It goes against the very idea of a collaborative community of inquiry. Each member of a CoI is assumed to embody some combination of the three qualities to varying degrees. In this scenario, neither the teacher nor the student exists separately. Each person has a unique set of obligations as both a teacher and a student (Akyol & Garrison, 2011, cited in Garrison, 2022).
- Learning presence was primarily associated with teaching and social presence, and the intersection of these presences is precisely where the perception of learning (i.e., cognitive presence) emerges (Maet al., 2017, cited in Garrison, 2017b).
- Adding new presences also risks increasing the framework's complexity and violating the principle of parsimony.

3.3.3.1 Learning presence

Learning presence (LP) is a characteristic that refers to the level of active participation. Shea et al. (2012) proposes learning presence as a new CoI element. More challenging learning tasks that encourage teamwork demonstrate learning presence connected with course grades (Shea et al., 2012). Active involvement, strong course engagement, and meaningful community interactions are crucial to learning presence. Shea and Bidjerano (2012) emphasise learning presence's CoI moderating role. It is regarded as one of the presences in the Community of Inquiry (CoI) framework, along with the presences of teaching, social and cognitive (Shea & Bidjerano,2010). The revised CoI is present graphical in Figure 3-5.

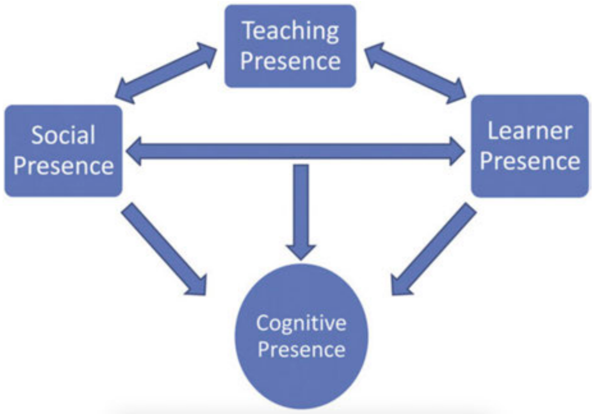

Figure 3-5.Revised community of inquiry model, including " learner presence”.

Source. Shea & Bidjerano (2010).

Shea (2010) argues that learning presence should be considered separate within the CoI paradigm since learner discourse frequently goes beyond the recognised social, cognitive, or teaching presence. Shea and Bidjerano (2010) defined learning presence as a concept that includes academic self-efficacy and cognitive, behavioural, and motivational variables. This highlights the significance of self-regulation in online learning contexts. Bandura's (1994, 1997) research on self-efficacy is ground-breaking, providing a basis for comprehending how individuals' perceptions of their ability to accomplish particular activities can significantly influence their behaviours and motives. The focus on self-efficacy corresponds to the concept of learning presence, which pertains to students' beliefs about their ability to effectively control and achieve success in their learning pursuits, particularly in self-paced and technology-driven educational environments like MOOCs. Given the crucial significance of self-regulation in student-centred teaching approaches, it is clear that students need to have robust self-regulatory abilities in order to succeed in blended learning environments and MOOCs. The study by Lee et al. (2019) provides insight into the many self-regulated learning mechanisms students utilise in MOOCs, encompassing motivational, behavioural, and contextual regulation. The need to acquire a learning presence within the Community of Inquiry (CoI) framework is emphasised by the independent nature of online learning, where students frequently have to navigate their educational paths with limited immediate guidance and support. According to Shea and Bidjerano (2010), and corroborated by Joo et al. (2013), persons who strongly believe in their abilities are more inclined to demonstrate practical self-regulation skills crucial for achieving academic success.

3.3.4 Educational experience

Education is a planned learning method that helps people to reach their goals quickly (Garrison & Vaughan, 2011; Yagcioglu, 2017). Education should be an opportunity to learn. The educational experience should change individuals' cognitive, affective and psychomotor domains; learning should reach the whole person. Educational experience should be active, practical, high-quality, deep, higher order, engaging, meaningful, systematic, collaborative and worthwhile in a convenient, cost-effective way. The proper steps must be taken to help students have positive experiences that lead to success (Garrison & Vaughan, 2008).

Garrison (2016) said that the educational experience is at the centre of the learning process because cognitive, social and teaching presences work together. Shea et al. (2010) later added a fourth presence (learning presence). CoI parts work together to create an educational experience, the exchange between the teacher (the subject expert) and the engaged community of learners (Garrison, 2017; Garrison & Vaughan, 2008). Learning must lead to an experience that changes how the learner and society act, regardless of its form. Therefore, any learning activity—lesson, course, or program—aims to have a learning experience. Any learning environment can use different activities, technologies, methods, and strategies to get students more involved. In formal education, like at a university, learning happens through activities that are planned and run by professors or facilitators. Even though learning is meaningful, teachers, students, administrators and society are dissatisfied with the quality of learning experiences (Garrison & Vaughan, 2008,2011).

Before the emergence of digital technology, the prevailing approach to education used conventional lectures, in which teachers conveyed material to pupils who received it passively. Nevertheless, in the present age of digital technology, where information is readily available through the internet, the effectiveness of traditional lectures as the exclusive means of training has yet to be doubted. Given the abundance of material accessible on the internet, educators are responsible for providing content beyond simple distribution and actively involving students in valuable learning encounters. Modern pedagogy responds to this change by emphasising incorporating technology-enabled instructional and learning approaches to support active student engagement and promote enhanced comprehension.

Garrison and Vaughan (2008) emphasise that higher education institutions acknowledge the significance of implementing technology-driven instructional methods to guarantee the pertinence and excellence of learning experiences. This requires the integration of various educational activities that utilise digital tools and resources, such as interactive simulations and real-life situations, to improve student engagement and understanding. Amidst the changing educational environment, students must actively involve themselves with course materials and partake in interactive learning activities to efficiently get information and skills.

Lessons should teach students to question their knowledge and think critically and creatively. Deep learning requires learners to be involved. Garrison et al. (2008) say that students want to learn in ways that are interesting and helpful to their lives. Higher education should offer exciting ways to learn concepts that meet the needs of a society based on knowledge. Garrison et al. (2008) say that this kind of learning atmosphere is the heart of higher education. They call them "communities of inquiry." People who are part of a community of inquiry do not have to be in the same classroom, building, or school. Technology has made it so that members no longer have to be in the same place. The Internet is essential for creating engaging learning experiences because it can connect learners far and near to form a learning community. Palloff and Pratt (2005) say that interactive and group learning are better for higher-order learning. When planned and carried out well, online and blended learning can be exciting ways to learn. Blended learning makes learning more engaging and compelling (Brown & Vaughan, 2018; Edel-Malizia et al., 2017; Garrison et al., 2008). The reason for this is that technology makes it possible for people to keep interacting after school is over. Different platforms offer different ways of doing things differently, including teaching and learning. E-learning could meet the needs of a knowledge society by creating and keeping active learning communities (Garrison, 2017). Blended learning and blended MOOCs provide the environment mentioned above for improving learning. Because of this, it is essential to study how students learn with the blended MOOC, which is one of the goals of this research. MOOC and localised LMS systems offer the much-needed environment for social interaction and personal reflection, which are essential parts of the learning experience that come from CoI. (Garrison & Akyol, 2015; Garrison et al., 2008).

As learners' experience depends on what they do, they must have the sanity to behave politely in academic or professional communities to reach their goals (Bryk et al., 2011; Garrison et al., 2008). In a school setting, the facilitator sets the goal for the whole community, so the person's reason for joining the learning community should be relegated to the background. For this kind of learning, one needs to listen carefully, explain and defend ideas and points of view (Garrison et al., 2008; Vaughan et al., 2013). In this learning environment, learners must work hard and be committed (Carlos, 2021; Garrison et al., 2008; Triquet et al., 2017).

Educational institutions use student representation, student feedback, teaching, learning, and assessment activities to improve the overall learning experience of all students (Little et al., 2009). The educational experience is made up of many different parts. "Engagement—interaction, cooperation and reflection—is at the centre of the educational experience," said the people who made the CoI. (Alebaikan, 2010; Garrison and Vaughan, 2008). Based on their study of student engagement, Little et al. (2009) found that higher education institutions see student engagement as a critical part of improving the student experience. Because of prior discourse, this study will focus on how engaged students are in their learning or educational experiences.

3.3.5 Community of Inquiry and Students Engagement

Students' engagement is key to the success of the CoI model. From Garrison and Vaughan (2008) made the following statements, which attest to that fact.

- Actively engaged learners provide the finest support for deep and meaningful learning experiences (p.x)
- Students demand a learning experience that is both relevant and engaging (p.x)
- Participating in a community of inquiry brings the public and private worlds together (p.16)
- Students were very satisfied with the course because of how well they got along with other students (p.32)
- Students value meaningful, applicable learning opportunities that encourage them to engage together (p.147).

Increasing student engagement in the classroom is a primary focus of online learning platforms in higher education. This participation is accomplished through constant communication, which develops both academic and social competencies (Ituma, 2011).

CoI for online learning can make students' engagement easier (Oyarzun & Morrison, 2013). Online education relies on a community of inquiry to promote active student participation (Shea & Bidjerano, 2010). This is achieved by encouraging students to participate in collaborative exploration and knowledge production through critical inquiry, reflection, and dialogue. As a result, students can better grasp and master the subject matter. The CoI promotes active engagement in academic pursuits and performance by establishing a nurturing atmosphere that fosters strong connections between students and their peers and instructors, encouraging meaningful interactions and collaborative learning opportunities. Students' engagement is vital for discovering knowledge to make learners active and instil lifelong learning capabilities in the digital era characterised by abundant information and learning initiatives, including MOOC.

How the students interact with their teachers and other students and what they are learning as community members is important (Anderson, 2017). Tools from e-learning systems like wikis, email, websites, discussion forums, chat and others make it easier for students to communicate with each other, content and teachers. Educational technologies help students in the same class or different classes, schools, or even countries in other parts of the world work together and as a team. Students can work together on projects, learn from their peers, or teach themselves before, during or after class lessons. Students can use tools like blogs to think about what they have learned in class and share it with the world. These activities make learning more interesting, so students at all levels can be helped by technology in their classes.

Student engagement and retention remain critical success indicators in higher education (Decker & Kunnen, 2018). However, online learning has considered problems inherent in retention and engagement (Lambert & Fisher, 2013). Learning is optimised when students are actively involved in the learning process, as active participation in educational activities is critical for a student's academic performance.

3.3.6 Community of Inquiry and blended MOOCs

The MOOCs used in the blended MOOCs by students in UCC are open educational resources (OERs) or courseware. Most students using such blended MOOCs preferred engaging individually with the videos and automated interactive elements but did not use the forums (Caulfield et al., 2013). Providing reasons for such behaviour, Caulfield et al. (2013) made the following:

- students had numerous other options to receive assistance and further instruction from local peers and instructors respectively;
- students primarily contact their local instructor, who also doubles as their MOOC local facilitator, to clarify any doubts as they interact with the content of the videos and reading materials.

Furthermore, Caulfield et al. (2013) stated that students do not need to contact other students in another country about a tough assignment when they have local classmates living very close by, while campus tutors can answer questions physically. Students in blended MOOCs are confronted with participating in the activities of either the MOOC or the on-campus course. However, the syllabus of the latter determines which activities are mandatory or optional. Once these determinations are made, students lead to higher academic performance, which may include avoiding the community features if they will not yield to awarding marks for them. Again, the difference in the workload, time zone, content of interest, and purposes among the blended MOOC users and the global MOOC cohort may be another reason why the former rarely used the community features of MOOC. Moreover, the local LMS's classroom sessions and discussion forums provide an authentic and reliable means of community building.

Since 2008, when Arbaugh et al. (2008) developed the Community of Inquiry (CoI) survey instrument, it has been validated for various EdTech solutions. However, some researchers believe that the instrument should be modified to suit the massive nature of MOOCs. This view is because it was initially designed for traditional small-scale online courses. Nevertheless, Kovanovi et al. (2018), after surveying 1,487 MOOC participants, concluded.

- CoI survey results were proven valid and accurate indicators of instructors' instructional, cognitive, and social engagement in MOOCs.
- It makes sense for the CoI survey instrument to be used in a MOOC environment.
- For example, it could be used to determine if the composition and design, the topic domain, or the number of students in the class affect the three levels of presence.
- The CoI Survey data can help us learn more about how people learn in MOOCs. It can also be used to evaluate and ensure MOOCs' quality from a pedagogical point of view.

In the blended MOOCs, there are three CoI presences that students think have a more substantial teaching presence (Saadatmand et al.,2017). To build and maintain a social and cognitive presence, one must learn how to teach presence in organisational and facilitating settings. It is essential to help students understand the course material (Garrison et al., 2010). As long as the design, facilitation and direction of teaching are given enough attention, a MOOC community of inquiry can be set up (Saadatmand et al.,2017). Writers say that a teacher's presence, course design and organisation, and role as a facilitator are all important parts of making a learning community that encourages students to connect (p. 72). Research shows that students are more interested in MOOCs if the teacher has certain qualities (Hew et al., 2018). People in MOOCs do not seem to care much about how important it is to talk to their peers. This difficulty demands interacting synchronously and asynchronously through forum posts and chat. There is a form of social presence in MOOCs as participants feel comfortable expressing themselves "like real people", but most do not view themselves as part of a community of learners (Stranach, 2017). MOOC designers and facilitators must encourage quality collaboration by designing assignments and other assessment and evaluation items. Such activities can improve social presence and educational experience (Stranach, 2017, p. 2).

3.4 Summary

The chapter examines technology adoption and the Community of Inquiry (CoI) approach in blended MOOCs. Section 3.2 discusses technological acceptance models, including the Unified Theory of Acceptance and Use of Technology (UTAUT) and its extensions, including UTAUT 2. The section examines performance expectancy, effort expectancy, and hedonic motivation to explore how these models affect consumers' intents and behaviours in adopting technology. Beyond technology adoption, the chapter explores online learning paradigms, focusing on the CoI framework in section 3.3. Beginning with the original CoI paradigm, which includes Cognitive Presence, Social Presence, and Teaching Presence, the section explores the new framework, incorporating Learning Presence. The chapter discusses how CoI principles affect blended MOOCs' collaborative learning and meaningful engagement in the section. The chapter also investigates how CoI principles might improve educational experiences in blended MOOCs. The next chapter deals with the conceptual framework of the study.

CHAPTER 4: THEORETICAL FOUNDATION AND CONCEPTUAL FRAMEWORK

4.1 Introduction

This chapter has a total of ten different parts. Section (4.2) deals with the theories that support the proposed conceptual framework. UTAUT 2 and CoI were the most critical parts of the study. Here is a short explanation of these parts and why they were given. Section 4.10 deals with the three moderators. In section 4.3, the discussion was focused on the parts of the conceptual framework. A brief discussion of each factor of the extended UTAUT leading to a reasonable hypothesis is discussed in section 4.4. The same is done for each of the elements of the enhanced CoI in section 4.8. Sections 4.5, 4.6, and 4.7 present the part of the framework that deals with the constructs that link UTAUT 2 and CoI, student engagement, and its results, which are student satisfaction and performance. The focus on how UTAUT 2 and CoI were brought together is deliberated in section 4.10.

This study evaluates how students' use and engagement in blended MOOCs will affect their satisfaction and perceived academic performance. The main research question was "how do students' use and engagement with blended MOOCs influence their academic satisfaction and performance". Since the study uses the combined models of CoI, UTAUT 2, and blended MOOC engagement, it examines the influence of the nexus of the models on students perceived academic performance and satisfaction with using the blended MOOC systems. The aim of the study can be seen from this perspective.

Most academic and grey papers prefer using the original CoI model with three presences (teaching, cognitive and social); however, this chapter justifies using four presences–including the learner's learning presence. Furthermore, task value replaces price value as one of the seven factors in the original extended UTAUT (UTAUT 2). Moreover, description is given to individual characteristics (sex, educational level and academic discipline) that serve as the moderators in the conceptual framework. They will moderate variables within the UTAUT 2 of the proposed model to study. The researcher will formulate the hypotheses and operational definitions for each construct will be briefly presented.

4.2 Theoretical Foundation

The rationale is that these two models have different levels of impact on student satisfaction and perceived academic performance with e-learning systems (blended learning and online learning). Some studies have argued that the CoI model has a higher level of student academic performance and satisfaction since it focuses more on student engagement (Aftab & Son, 2020; Kazanidis et al., 2018). Others have noted that its reliance on cognitive, social, teacher and learner presences give a more robust assessment of a student's educational experience, ultimately leading to higher satisfaction and performance (Kaul et al., 2018; Aftab et al., 2020). However, similar claims have been made for the UTAUT 2 model (Chao, 2019; Al-Saedi et al., 2020).

All these assumptions vary in measuring students' perceived academic performance and satisfaction. Since COI and UTAUT have different impacts on students' academic satisfaction and performance, this study argues that COI focuses on educational experience as a precursor to and determinant of academic satisfaction and perceived academic performance as underpinned by experiential learning theory. Similarly, UTAUT focuses on behavioural intentions as a precursor to the actual use of an online learning system, which should ultimately achieve academic satisfaction and perceived performance learning goals. The general knowledge in literature is that experience (depicted in this research as students' engagement) of a system is attained if there is the actual use of the system (Al-Saedi, & Al-Emran, 2021). Students' actual use of the blended MOOC system should be evident in their engagement, leading to academic satisfaction and perceived academic performance. It is akin to Jadil et al.'s (2021) definitions of experience as the practical knowledge and familiarity produced by these conscious processes. Stated differently, it is the practical contact with and observation of facts or events based on the actual use of interaction (Pati et al., 2020). Based on these assessments, the study examines the effect of the UTAUT on the COI model to determine the extent of their impact on students perceived academic performance and satisfaction with the blended MOOC system.

The theoretical underpinning of the conceptual framework for the nexus comes from various theories. These are the theory of academic performance, need performance theory, theory of student engagement, social learning theory, cognitive theory, self-efficacy, expectancy-value theory and behavioural theory.

Elger (2007) supposes that performance is affected by several factors. Since a person's level of performance and the attribute they gain are directly related, it is easier for them to move up the performance levels. According to Elger (2007), when an individual's performance level shifts, three key characteristics emerge: 1) an improvement in quality, competence, knowledge, skills and motivation; 2) an improvement in one's sense of self, and 3) a reduction in expense. Elger (2007) further stated that immutable and non-immutable factors influence an individual's performance. The non-immutable factors that can be varied fall into three categories.

- "Mindset" is linked to a student's interest and success in a subject or activity. When a student is not interested in learning, they are less likely to show up to class every day, which affects their grades directly. The mindset of students concerning blended MOOCs differs.
- Environment. One's immediate surroundings have a significant effect on how productive they are. As a result, things outside of a person can affect how well they do (Elger, 2007). Because of the combination of MOOC and classroom, the blended MOOC environment may produce a good or bad result for computer-loving and computer-phobic students, respectively.
- "Reflective Practice". With this, a person predicts people's future success from their experience, prior knowledge, skill level, or lack of skill (if any). For example, with the blended MOOC system, technologically savvy and autonomous students may have advantages in the technology and course sessions that are not facilitated under their control.

McClelland (1961) and Atkinson (1974) originate the need and performance theories. The need-accomplishment approach aims to explain why some people are motivated to succeed while others are not. From experience, when the instructor tells the students that the mode of instructional delivery is a blended MOOC strategy, some students are excited, especially those who are digitally savvy. On the other hand, others are not, especially those not digitally savvy. These theories are based on two essential parts of human nature: the need to succeed and the need to avoid failure. This theory is called the "approach-avoidance model" because it says that a person's motivation to (a) engage with (approach) a situation or (b) run away from (avoid) it depends on how vital two factors are. People will do something if they want to do it for themselves, and their desire is more potent than their fear of failing. However, people will avoid or stop doing the work if they fear failing more than they want to do it on their own. If the chance of success is high and the reward for success is big enough, even someone who is not very self-motivated may be driven to succeed. This theory posits a potential explanation for the inclination of "high achievers" to pursue complex tasks, as they perceive intrinsic worth in attaining success in intricate and challenging endeavours. Additionally, this elucidates the rationale behind an individual categorised as a "low achiever" to opt for less demanding tasks since they are less likely to fail and more likely to be finished successfully.

Also, Yüksel and Yüksel (2001) say that the disconfirmation paradigm is based on how people feel about a service encounter based on whether their expectations were met or not. The confirmation or disconfirmation of expectations characterises that. The principle of disconfirmation says that when a customer has a new service experience, they compare it to a benchmark they already know. When they compare the service to this benchmark, they will form an opinion about how good it is. When a service is done the way, it was promised, that is confirmation; however, disconfirmation results when there is a difference between performance and expectations. Students are to compare their experiences with blended MOOC with the traditional classroom environment, which is their known benchmark. The assumption is that when given alternative learning environments–classroom, blended learning, fully online, blended MOOC and MOOC, the student's decision will be based on this theory. They should choose one of these according to whether the environment meets the learning expectations or not.

Astin's (1984; 1999) theory regarding student engagement is also present. According to the theory, increased student engagement in their college experience positively correlates with enhanced individual learning, personal growth, and academic performance. The theory's central premise is that the success of any given educational practice is proportional to the extent of improving student engagement by making students more interested in learning. The amount of time and effort students put into their studies is what is meant by "student involvement or engagement." Therefore, a highly engaged student spends much time in class, joins many student groups, and tries to get to know their instructors and other students. On the other hand, an unengaged student usually does poorly in school, does not go to school very often, does not do any extracurricular activities, and does not talk to teachers or other students very often. The engagement theory is made up of five main points:

- Students’ engagement is described as putting psychological and physical effort into a subject or their activities.
- A student's interest in an item or topic varies from person to person and over time.
- Being engaged has both quantitative and qualitative parts. For instance, a student's commitment to their studies can be judged quantitatively and qualitatively. The quantitative dimension concerns, for example, how many hours students spend studying. On the other hand, the qualitative aspect deals with how students feel about their studies, e.g., whether they do surface or deep reading. Thus, a mixed research method should have been employed for this study. However, only the quantitative method will be used. Quantitative methods use numerical data, which may not fully represent students' subjective experiences and impressions. Students' motivations, learning preferences, and obstacles during blended MOOCs may be overlooked by relying primarily on quantitative evaluations.
- The number and quality of students participating in an educational programme determine its success.
- The success of a teaching method or strategy depends on how well it can get students interested.

The main idea behind the experiential learning theory is that individuals need to have personal experience with a subject matter to understand it fully. According to Kolb (1984, cited by Sharlanova, 2004), when individuals learn something new, they construct it out of pieces of knowledge that they have picked up in the past. Thus, this kind of learning experience takes centre stage and can be positive or negative. For experiential learning to occur, there is the need for the learner to exhibit a high level of engagement comprising affective, behavioural, collaborative, cognitive, emotional, physical, physiological, social and spiritual. Thus, learners involving learning by experiencing must immerse themselves wholly into the learning process to obtain the desired outcome. Because of its long history, the diversity of the concept and its involvement that deals with the whole person, the definition of experiential learning has been evolving. Thus, learners should be able to confirm whether or not their experience using a learning system or EdTech solution met their desired academic satisfaction and perceived performance expectations.

Albert Bandura, a psychologist, proposed the concept of social learning, which is based on watching what other people think, do, and say and then copying them (Cai & Chi, 2021). It considers how an individual's surroundings –beliefs and worldviews–might affect their ability to learn and behaviour to find their place in the world and society.

According to the cognitive development theory proposed by Jean Piaget, children progress through four distinct stages of learning, with the final stage being the Formal Operational stage, which typically occurs from the age of 12 and onwards (Cherry, 2022). Students' intellectual abilities and activities transform their maturation process. Students' cognitive development encompasses more than mere acquisition of knowledge; it also necessitates the construction of mental representations of the surrounding world (Miller, 2011). Piaget's research serves as the fundamental basis upon which constructionist theories are grounded. Constructionists hold the belief that knowledge is actively constructed, and the process of learning takes place when children engage in the creation of tangible products or artefacts. Learners are more inclined to actively participate in learning when the educational materials and resources are personally relevant and imbued with meaning. Students' self-efficacy is confidence in their abilities to do the things that will lead to the desired results (Bandura, 1997). The idea looked at how important it is for people to believe in their abilities. Self-efficacy measures how sure someone is that they can change their motivation, behaviour and social environment. Theoretically, individuals can figure out the following on self-efficacy. 1) Some people have a high level of self-efficacy, while others do not; 2) some people have a broad view of their efficacy, while others have a narrow one; and 3) some people think they can do well in even the most challenging jobs, while others think they can only do well on easier ones. It considers how a person's environment and thoughts can affect their ability to learn and how they act. It considers how one's surroundings and thoughts might affect one's ability to learn and behave. In the expectancy-value model of performance motivation, success expectations and the value of each task are important factors (Dietrich et al., 2019). The expectancy-value theory asserts that students' decisions about performance and performance itself are primarily based on their expectations for the future and their viewpoints of the tasks at hand (Eccles & Wigfield, 2002). The expectancy-value theory of accomplishment motivation says that how important a task is seen to be is a big part of whether or not it will be done. Expectancy refers to how confident individuals are in their ability to succeed. How probable can a wanted outcome be achieved through the behaviour or action?

Task values are people’s opinions about how important, useful, or fun activity is to them. How much does the individual value? Subjective task value can be considered the motivation that allows an individual to answer the question, "Do I want to do this activity and why?” (Dietrich et al., 2019; Wigfield & Cambria, 2010).

A person's expectation beliefs include task-specific success expectations (how well they believe they can execute the job) and broader views about their competence in a given specialisation domain (i.e., their self-concept of ability). (Eccles & Wigfield, 2002; Dietrich et al., 2019). A task's intrinsic, performance and utility values and the costs associated with not completing it are three of the task's four motivational components (Eccles & Wigfield, 2002; Dietrich et al., 2019). Several studies have found that an individual's degree of anticipation and value interaction with their employment strongly predicts important outcomes like engagement, continuing interest and academic performance. Trautwein et al. (2012), Nagengast et al. (2011), and Eccles (1983) are examples of studies that support this viewpoint. The main idea behind the behavioural theory is that all behaviours are learned by interacting with their environments. This way of thinking indicates that a person's upbringing and genetic makeup have little effect on their habits and behaviour (Murray, 2022).

Figure 4-1depicts how the various constructs discussed so far are interlinked in the conceptual model for the study.

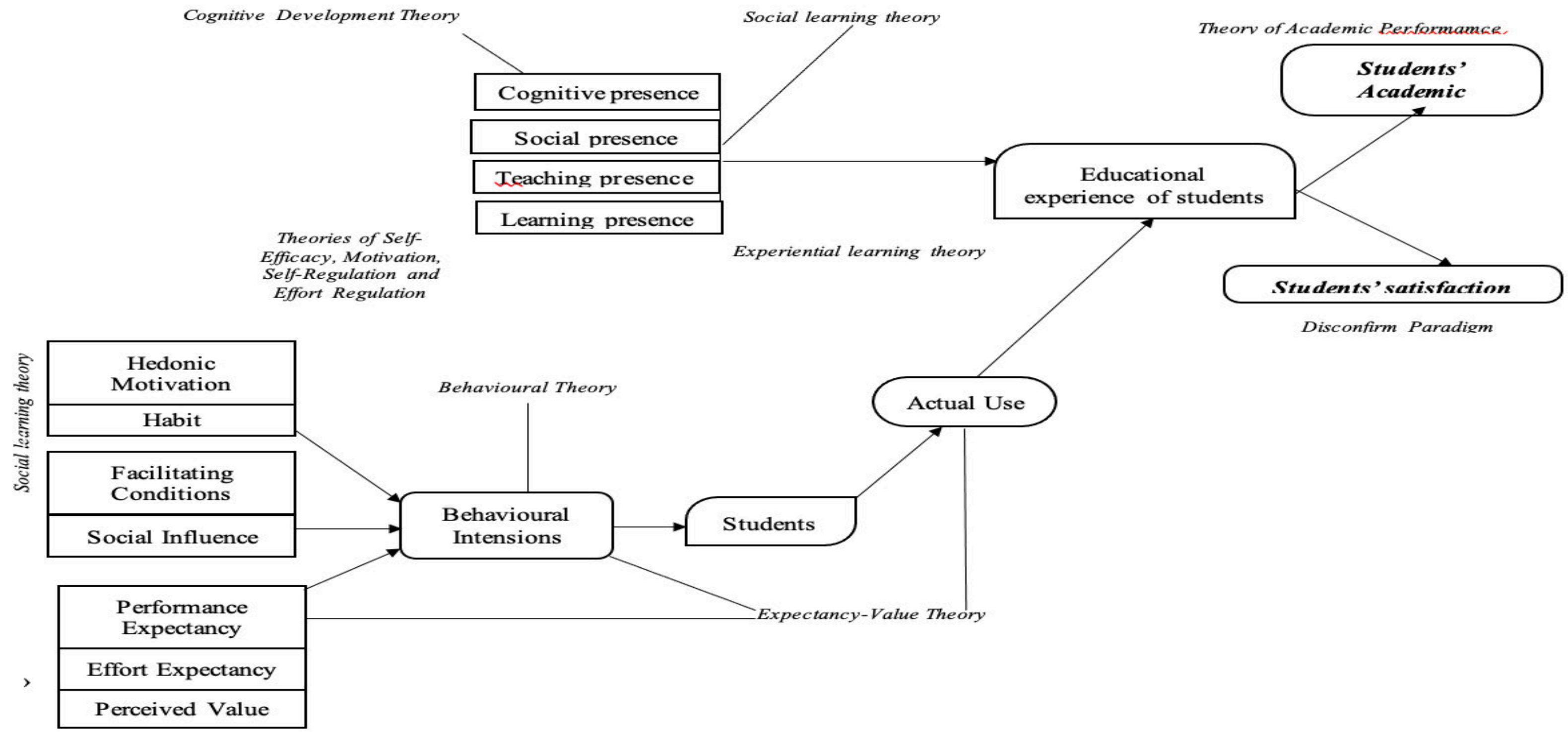

Figure 4-1.The proposed Conceptual Model.

4.3 Conceptual Framework

The framework can be decomposed into three parts; 1) the interaction among the seven factors of the UTAUT model; 2) the interaction among the four presences within the CoI; 3) the association between the UTAUT and CoI models. The exogenous variables for the framework are actual use (AU) and students' engagement (SE). These are the outcomes from the models that form the combined model of the study framework. Again, the endogenous variables are students' satisfaction (SS) and perceived academic performance (AP).

4.3.1 UTAUT 2 factors for the study

As indicated earlier, Venkatesh et al. (2012) revealed that all seven factors (PE, EE, SI, FC, H, HM, and PV) predict BI and FC, H, and BI predict AU in UTAUT 2. However, different apps/technologies and/or study populations result in distinct conclusions.

4.3.1.1 Performance Expectancy

Users' willingness to adopt new technology, especially if it improves job performance, depends on their impression of how a system should work. Performance expectancy (PE) regularly affects behavioural intentions (BI) and actual behaviour (Tarhini, 2016; Vermaut, 2016; Sair & Danish, 2018; Chao, 2019). Some research shows a strong link between PE and BI (Bellaaj, Zekri, & Albugami, 2015; Salloum & Shaalan, 2018). Bellaaj et al. (2015) and Tarhini (2016) claim that PE immediately affects BI because users expect new technology to outperform its predecessors in functionality and value, driving continued system usage.

PE has been studied in many technological situations, but contemporary research has focused on e-learning. Merandu et al. (2019) found PE to be the strongest predictor of intention to use online learning platforms, whereas Mendoza et al. (2017) found it to be a major factor in MOOC enrolment. PE affects intention to use, although Vermaut (2016) implies it may not be the most important factor. In MOOCs, PE has a significant but not dominant effect on users' intention to use the platforms (Mulik et al., 2012; Fianu et al., 2018). PE plays a role in shaping behavioural intention, although it is minimal compared to effort expectancy, social impact, facilitating conditions, and trust in Internet banking uptake, according to Foon and Fah (2011).

From the above-named studies, there is a lack of research on blended MOOCs. Prompting this study to examine how PE affects users' behavioural intention to use blended MOOCs, thereby providing a comprehensive understanding of PE and behavioural intention in blended MOOC adoption.

Therefore, the researcher hypothesised:

H1: Performance Expectancy (PE) will significantly affect behavioural intention (BI) using the blended MOOC system.

4.3.1.2 Effort Expectancy

Sair and Danish (2018) define effort expectancy (EE) as technology use's perceived easiness. It measures how easy or difficult people find technology use, indicating system interaction's ease and adaptability. According to the study, students' intentions to adopt technology are strongly influenced by their perceived ease of use. Attuquayefio and Addo (2014) discovered that EE was the only predictor of students' behavioural intention to utilise ICTs for learning in the UTAUT. Birch and Irvine (2009) and Chao and Tung (2008) agree that EE is the most significant influence on system consumption.

According to Chesney (2006), Fianu et al. (2018), Radovan and Kristl (2017), and Alharbi (2017), users' effort expectancy perceptions sometimes match their usage behaviour. Chesney (2006) found a disparity between users' system effort expectations and actual behaviour. Fianu et al. (2018) found no correlation between MOOC intention and social influence or effort expectations. Like Radovan and Kristl (2017), perceived e-learning difficulty did not affect utilisation. Alharbi et al. (2017) found that instructors' effort perceptions affect mobile learning adoption in higher education.

These differing views highlight the need for future research into effort expectancy and system usage behaviour, particularly in blended MOOC adoption. Despite advances in LMS that claim to improve user-friendliness and minimise effort expectancy, gaps remain in researching how students' views of ease of use affect their desire to embrace blended MOOCs. To fill these gaps, this study examines the direct relationship between effort expectancy and behavioural intention in blended MOOC uptake.

As a result of this preceding discussion, the researcher hypothesised the following:

H2: Effort Expectancy (EE) will significantly influence the behavioural intention (BI) to use a blended MOOC System.

4.3.1.3 Social Influence

Defining social influence (SI) is difficult since it is normative in groups and informative in individuals (Palau-Saumell et al., 2019; Perfumi, 2019). SI affects behavioural intention (BI) in technology adoption (Venkatesh & Morris, 2000; Venkatesh & Davis, 2000; Park, 2009), but its direct effect on BI is inconsistent, especially in educational technology settings like MOOCs.

SI's impact on blended MOOC adoption is even more ambiguous (Fianu et al., 2018; Mulik et al., 2018). Given the compulsory character of the blended MOOC under research, this study examines how SI affects the intention to use blended MOOCs to fill a vacuum in the literature on SI's conditional impacts in mandatory education. This study critically analyses existing research to understand better SI's impact in compulsory blended learning environments, where it may differ from its impact in voluntary contexts (Venkatesh & Davis, 2000).

As a result of this preceding discussion, this study hypothesised the following:

H3: Social influence (SI) will significantly influence a student's behavioural intention (BI) to use the blended MOOC system.

4.3.1.4 Facilitating Conditions

Facilitating Conditions (FC) include trust in system-supporting human, organisational, and technological resources (Venkatesh et al., 2003). FC refers to learners' impressions of platform resources for navigation and use in blended MOOCs. Technology, including personal computers, broadband connectivity, accessible networks, and network security, are necessary for effective learning system participation (Fu et al., 2006; Taylor & Todd, 1995).

MOOCs require human, organisational, and technical resources in educational settings. Students and teachers need various resources and tools to use such platforms, with additional resources often needed to improve usersatisfaction. FC affects user behaviour because favourable conditions encourage technology uptake and use. Khechine et al. (2020), Mensah (2019), and Jewer (2018) found that FC predicts user intents in modified UTAUT models. Chang et al. (2007) and Limayem & Hirt (2000) showed no statistically significant relationship between FC and behavioural intention; however, they discovered an impact on actual usage.

FC is crucial in blended MOOCs because it affects learners' system resources and support perceptions. Internet and mobile technology infrastructure might facilitate or discourage blended MOOCs for teachers and students. FC's value is enhanced by institutional support, which pushes stakeholders to use innovative learning methods. The study analyses the association between FC, behavioural intention (BI), and blended MOOC actual use (AU). The research examines students' views of system resources and support to measure FC's impact on blended learning platform adoption and use. This analysis intends to show users' participation with blended MOOCs and improve higher education learning experiences. This study would corroborate this assumption for understudied blended MOOCs. FC must be reviewed to see if blended MOOCs' BI and AU are affected. This study will quantify FC by students' perception of their blended system resources and support.

As a result of this preceding discussion, this study/the researcher hypothesised the following:

H4: Facilitating conditions (FC) will significantly influence the blended MOOC system's behavioural intention (BI).

H5: Facilitating conditions (FC) will significantly influence blended MOOCs' actual use (AU).

4.3.1.5 Habit

Triandis (1971, as cited in Chang, 2012) defined habit as an unconscious behavioural pattern. Technology usage habit can be defined as past behaviour or automaticity (Chang, 2012). In mobile teaching-learning, habit predicts the intention to use mobile internet and influences actual usage, according to Nikolopoulou et al. (2021). Wong et al. (2020) revealed that teachers' frequent use of technology positively influenced students' and instructors' behavioural intentions (BI).

Habit formation is greatly influenced by software applications (Oulasvirta et al., 2012) and is crucial to IS adoption. Habit was the best predictor of intention to use and actual usage in the UTAUT model, according to Escobar-Rodriguez & Carvajal-Trujillo (2014). However, Limayem et al. (2007) suggested that habit influences technology use more than intention.

Despite these observations, the effect of habit in blended MOOCs is still unclear. Research has shown the importance of habit in technology, but its effects on blended MOOC uptake are unknown. This study examines how habit affects blended MOOC intention and use to fill this gap. This study synthesises and critically analyses related material to reveal the unique dynamics of habit building in blended MOOC uptake.

As a result of this preceding discussion, the researcher hypothesised the following:

H6: Habit (H) directly and significantly affects the intentions (BI) to use blended MOOCs.

H7: Habit (H) directly and significantly affects blended MOOCs' use (AU).

4.3.1.6 Hedonic Motivation

Hedonic motivation—perceived pleasure in IS/IT research—has been found to affect technology adoption and use (Chang, 2012). Technology use should bring joy, enjoyment, or pleasure (Venkatesh et al., 2012). Hedonic motivation correlates with human motivation theories, where people adopt new technology for enjoyment (Yang, 2013).

Literature shows that hedonic motivation drives client acceptance and utilisation of new technology (Brown & Venkatesh, 2005). In information systems studies, it predicts technology use (Alalwan et al., 2017). The overwhelming support for hedonic motivation in mobile technology adoption strengthens its importance (Alalwan et al., 2017; Nikolopoulou, 2021). In mobile learning/teaching adoption research, students and instructors have recognised the importance of hedonic motivation (Yang, 2013; Nikolopoulou et al., 2021).

This research synthesises and critically analyses related material to better understand the adoption of e-learning. Despite substantial studies on hedonic motivation in numerous technology contexts, its effects on adopting blended MOOCs still need to be determined. This study examines how hedonic motivation affects blended MOOC intention and use to fill this gap.

As a result of this preceding discussion, this study/the researcher hypothesised the following:

H8: Hedonic motivation (HM) significantly and significantly affects behavioural intention (BI).

4.3.1.7 Task Value

The notion of task value is crucial in educational technology uptake, particularly in the context of blended MOOC systems. Task value, as conceptualised by Zimmerman (2011), impacts a student's choice to engage in a school project based on how significant they think it to be for their future performances. Eccles and Wigfield (2002) delineate the constituents of task value as follows:

- intrinsic value (pleasure derived from the task)
- utility value (relevance of the task to goals)
- performance value (significance of the task to one's identity)
- cost (possible adverse outcomes associated with the task)

Chiu & Wang (2008) propose the inclusion of task value in the UTAUT model, asserting that task value is crucial for accurately forecasting the adoption of web-based learning. Their position is bolstered by empirical evidence demonstrating a robust correlation between the perceived importance of a task and academic performance. For instance, Campbell (2007) discovered a positive association between task value and performance in courses regarded as crucial for students' future professional endeavours. The significance of task value extends to its ability to forecast satisfaction and performance in online settings (Joo et al., 2018) and its impact on student-teacher relationships (Yang et al., 2006). Bures, Amundsen, and Abrami (1998) and Lee (2002) provide additional evidence supporting the correlation between higher task value and better satisfaction with online learning.Chiu and Wang (2008) found that the subjective value of a task has a considerable impact on the intention to use web-based learning, which is on par with performance and effort expectations.

In order to successfully implement blended MOOCs, it is crucial to ensure that the tasks align with the students' perceived value, taking into account their inherent, practical, and performance-related features while also minimising expenses.Hence, it is essential to ascertain whether students believe the task value associated with blended MOOCs would facilitate their acceptance and utilisation of this instructional approach.

As a result of this preceding discussion, this study hypothesised the following:

H9: Task value (TV) will have a direct positive impact on the student's intention (BI) to use the blended MOOC system.

4.3.1.8 Behaviour Intention

The intention to use, or behavioural intention (BI), is crucial to understanding technological uptake and usage. It indicates a person's readiness and willingness to act in the future (Khechine & Lakhal, 2018). Numerous models of technology use anticipate that a strong intention often leads to action, especially when the behaviour is under the individual's control (Taiwo, 2019; Venkatesh et al., 2003). Williams et al. (2015) found a 0.82 predictive power between BI and usage behaviour in most articles reviewed.

The relationship between intentions and actions is not always clear. Celik (2016) and Khechine and Lakhal (2018) found that intentions affect behaviour most when modified or mediated by other variables. These data suggest that the predictive value of behavioural intention may vary, casting doubt on its universal applicability (Jeyaraj et al., 2006). While objectives may motivate students to take MOOCs, ease of use may moderate this association (Woon, 2019). Behavioural intention affects system utilisation in mobile teaching and learning (Nikolopoulou et al., 2021). This implies that intention-induced confidence can lead to system use.

This study builds on past research by evaluating direct and indirect factors impacting behavioural intention and use behaviour. This research seeks to understand the blended MOOC's intention-behaviour dynamics, with the possibility of disclosing underexplored parts of the intention-action link. Such disclosure may contribute to knowledge by identifying settings under which behavioural intention most consistently predicts educational technology usage behaviour.

As a result, the researcher hypothesised the following:

H10: Students' behavioural intention (BI) will significantly affect their actual use (AU) of blended MOOCs.

4.3.1.9 Actual use of blended MOOCs

An individual's plan to continually engage with a system based on positive early experiences is called 'actual use' or 'continuation intention'. This long-term use is crucial for educational technology, especially blended MOOCs (Bhattacherjee & Premkumar, 2004). Joo et al. (2018) defines continuation intention in MOOCs as persistent engagement with the MOOC format, not course completion. The many learners wanting to enrol in subsequent courses characterise a successful MOOC platform. Bhattacherjee (2001) proposed that initial gratification leads to frequent use of new technological systems through continuance intention. Durable blended MOOCs assume that learners' satisfaction with first interactions affects their long-term engagement with technology. MOOC students' long-term engagement and motivation are captured by continuation intention. Studies sometimes need to pay more attention to ongoing engagement and emphasise initial enrolment (Huang et al., 2017; Wu & Chen, 2017).

Understanding what keeps students using blended MOOCs after the initial appeal fades is critical to long-term success. Research shows that a variety of factors, from learner characteristics like personal history and interests (Jordan, 2015; Tseng et al., 2016) to MOOC platform features like accessibility and interactive design (Alraimi et al., 2015; Davis et al., 2017), affect continuation intentions. Research has shown that user perception, self-efficacy, and satisfaction affect MOOC retention.

This study examines the complex factors that sustain MOOC engagement to build on previous studies. It examines how psychological traits and technology variables affect learners' long-term MOOC engagement. The study addresses research gaps to improve knowledge of blended MOOC continuation intention dynamics and provide actionable insights to optimise blended MOOC platform design and execution for continued use.

As a result of this preceding discussion, this study hypothesised the following:

H11: Students' use (AU) of blended MOOCs will significantly affect their engagement (SE).

4.4 Elements of the community of inquiry for the study

The blended MOOC that this research is based on has the assigned traditional roles of teachers and students. However, study subscribed to the student-centredness of the MOOC, hence the inclusion of the learning presence in this study.

4.4.1 Teaching Presence

According to research, TP is necessary for course structure, interaction, and active learning (Wehlburg, 2022; Anderson et al., 2001). Though critical, empirical studies on TP and students' overt participation in virtual classrooms are limited (Zhang et al., 2016). TP may positively affect student engagement, although the link is complex and inconsistent (Hung & Chou, 2015; Zhang et al., 2016). TP must be improved to create a friendly learning environment and increase student participation in blended MOOCs. This study hypothesises that TP will be a crucial predictor of engagement within the Community of Inquiry framework (Arrufat et al., 2015).

This study addresses the following information gaps. Previous research reveals a favourable correlation between TP and engagement, but the degree is unclear (Zhang et al., 2016). This study examines the degree and direction of this link in blended MOOCs. Current research focuses on how TP affects students' perceptions rather than their participation (Zhang et al., 2016). This study examines how TP affects passive, active, constructive, and interactive student engagement in blended MOOCs. TP is important in online learning, but its relevance in blended MOOCs has yet to be discovered. This study examines how TP influences engagement in this learning environment.

From the above discourse, this study proposed the following hypothesis:

H12: Teaching presence (TP) will significantly impact students' engagement (SE) in the blended MOOC system.

4.4.2 Cognitive Presence

Several studies highlight the potential of EdTech solutions in fostering CP and engagement. For instance, Cui & Wang (2023): Social annotation tools promote active learning and communication, vital elements of CP, ultimately enhancing knowledge construction and engagement. Salhab (2023): Mobile learning enables flexible and accessible knowledge co-construction, shaping CP and boosting engagement in technology education. These studies underscore the transformative potential of EdTech in creating interactive, supportive, and student-centred learning environments that nurture CP and engagement. However, Kozan and Richardson (2014): Meta-analysis reveals inconsistencies in CP measurement across studies, questioning the validity of findings supporting its direct impact on outcomes. Again, Margaryan et al. (2015) and Wilson & Berge (2023) suggest that CP effectiveness depends on various factors beyond its presence. These perspectives call for a more comprehensive understanding of online learning success that goes beyond CP alone.

These findings indicate that cognitive presence may not be a panacea for e-learning success and depends on other elements. By examining these issues, educators and researchers can gain a more profound knowledge of e-learning success beyond cognitive presence This study expands on previous studies and addresses weaknesses. Explore the unique CP-EdTech dynamics in blended MOOCs, a burgeoning but underexplored instructional delivery technique. This research uses contextual elements, and EdTech implementations in a blended MOOC to better understand CP's function in online learning.

From the above discourse, this study proposed the following hypothesis:

H13: Students' cognitive presence (CP) improves blended MOOC engagement (SE).

4.4.3 Social Presence

The academic community has studied the relationship between students' social presence and technology engagement from several aspects. Imron et al. (2023) note that social media may motivate, engage, and transform learning environments. Their research on social media-based English language learning models can improve students' social presence and engagement. Increased social contacts through technology are linked to improved student engagement, supporting the idea. In contrast, Wagner, Pishtari, and Ley (2023) compare on-site and remote students' usability evaluations, social presence, engagement, and learning in a synchronous hybrid situation. Their findings imply that social presence's impact on engagement may vary by learning context and delivery mechanism. This contradicts the notion that social presence has varying effects on engagement in various educational environments. Bekele and Amponsah (2023) employ technology in higher education ecologically. They believe social presence and interaction are essential to technology-enhanced learning's ecological system. Research highlights that the impact of social presence on engagement depends on its integration with instructional design and technical infrastructure.

The debate shows that social presence improves student engagement in technology-enhanced environments, but the relationship is complex and influenced by many factors. These include technological design, pedagogy, subject matter, and learner differences. These studies show that the theory is true in some settings but must be addressed within a broader educational framework. While SP is studied in many contexts, a better knowledge of its effects in blended learning and specific blended MOOCs is needed. How SP interacts with instructional design, technology infrastructure, and learner characteristics to affect engagement needs further study. Investigating SP's optimal engagement conditions can help educators and instructional designers develop tailored tactics.

From the above discourse, this study proposed the following hypothesis:

H17: The students' social presence (SP) will significantly influence their engagement (SE) in the blended MOOC system.

4.4.4 Learning Presence

Students with high self-efficacy use better self-regulation skills and engage more with learning tools (Bandura, 1997; Zimmerman, 2000). Self-efficacy promotes self-regulated learning in online environments, increasing engagement, according to Doo and Bonk (2020). Self-efficacy and self-regulated learning practices also predicted MOOC engagement and success, according to Lee et al. (2019). The relationship between self-efficacy, self-regulation, and student technology use has critics and complexities.

Some researchers believe that instructional design, technology, and learner variations may moderate the effect of self-efficacy and self-regulation on engagement.

Kirschner and Karpinski (2010) propose that technology distractions may negate the benefits of self-efficacy and self-regulation, especially for disengaged students. Evidence also shows that self-efficacy and engagement may be more complex and universal. Rienties and Toetenel (2016) examined learning analytics data from an extensive online learning platform and found that self-regulation tactics increased engagement on average, but student engagement varied. This suggests that digital engagement may not boost academic performance for some students, particularly those with poor self-efficacy. The argument over self-efficacy and self-regulation in technology engagement highlights the complexity of digital learning. While theoretical and empirical research suggests that these psychological dimensions shape students' technology use, their impact depends on several aspects. The learners' prior technology experiences, teaching methodologies, and digital tools and platforms are factors.

The premise that students' self-efficacy and self-regulation significantly affect their technology engagement is valid but must be contextualised within the educational ecosystem. Future studies should use various methods to understand the numerous aspects that affect technology-enhanced learning. Based on this narrative, learning presence—including technology self-efficacy and self-regulated learning—does increase student engagement in different contexts. However, this relationship is contentious. This debate highlights the complexity of digital learning, suggesting that learning presence (self-efficacy and SRL) affects technology engagement through various factors, including instructional design quality, technology type, and learner differences. Given these factors, the claim that students' learning presence (self-efficacy and self-regulation) significantly affects their digital engagement must be contextualised within the educational ecosystem. This viewpoint invites further study of these relationships within blended MOOCs.

From the above discourse, this study proposed the following hypothesis:

H15: The students' learning presence (LP) will significantly impact their engagement (SE) in the blended MOOC system.

4.5 Engagement, Satisfaction, and Performance in Blended MOOCs

Effective online education thrives on active student participation, a cornerstone for engagement and learning outcomes (Rajabalee et al., 2020). A robust assessment of curriculum efficacy utilizes direct performance indicators, such as tests, projects, and presentations, alongside indirect measures like student satisfaction to gauge comprehensive educational impact (Tessema et al., 2012). The significance of the teacher's presence in enhancing student engagement and satisfaction underscores the intertwined roles of instructional methods and technology in facilitating learning (Garrison et al., 2000; Jaggars, 2013).

The dynamic relationship between student engagement and academic performance suggests a virtuous cycle, where enhanced engagement leads to improved performance, further fueling engagement (Lei et al., 2018). This reciprocal influence highlights the pivotal role of student engagement in achieving educational success and satisfaction, laying a foundational premise for investigating blended MOOCs.

The research underscores the positive effects of EdTech-driven learning on engagement, perceived academic performance, and satisfaction (Fisher et al., 2021). Specifically, MOOCs have been shown to elevate participant satisfaction and performance by 15%, pointing to the potential of technology-enhanced learning models (Koller et al., 2013). This finding predicates that engagement with blended MOOC systems significantly influences student satisfaction and performance, necessitating a focused investigation into blended MOOCs. A well-constructed blended learning course, characterized by its engaging content and support for learning outcomes, can elevate student satisfaction, engagement, and academic performance (Kahu, 2013; Pye et al., 2015; Yearwood et al., 2016). Supporting this, a meta-analysis involving 196,473 participants revealed a significant positive correlation between student engagement and academic performance, reinforcing the need to explore these dynamics within blended MOOC environments (Lei et al., 2018).

Given the established benefits and the emerging significance of blended MOOCs, this literature supports investigating the relationships between student engagement with blended MOOC systems and their satisfaction and perceived academic performance. By critically examining existing research, this study aims to identify gaps and explore new areas within blended MOOCs, thereby contributing to a deeper understanding of their impact on educational outcomes.

Because of the preceding discourse, the researcher hypothesised that:

H16: Students' engagement (E) with the blended MOOC system will significantly influence their satisfaction (SS).

H17: Students' engagement (E) with the blended MOOC system will significantly influence their performance (AP).

4.6 Combining UTAUT 2 and CoI

Several studies have supported a situated approach to technology acceptance and shown that context characteristics affect user beliefs (Doleck et al., 2018; Lemay et al., 2017; Lemay et al., 2018). In this point of view, situational determinants, more than core technological factors, influence technology acceptance judgements. The situational determinants in Lemay et al. (2018)'s study were the CoI model's social, cognitive, and teaching presences in an educational context. Lemay et al. (2018) used the TAM and COI to find that the teaching component, mediated by the social and cognitive dimensions, strongly influenced e-learning acceptance. According to Lemay and colleagues, e-learning settings with high teaching, social and cognitive presence can increase acceptability (Lemay et al., 2018). The presence of social, cognitive, or teaching factors may contribute to the variance in technology acceptance, as suggested by Lemay et al. (2018). Again, the situational factors influencing the acceptance and use of Snapchat were passion and privacy concerns (Lemay et al., 2017). The situated perspective on technology acceptance provides a complete account of technology, thereby providing strong explanatory power. In all the above instances, TAM was used as the acceptance model.

Few studies have been conducted combining the elements of CoI and UTAUT. Radovan and Kristl (2017), one such paper combining UTAUT and CoI to determine the factors or aspects of CoI that are most predictive of whether or not teachers at the University of Ljubljana will be prepared to use learning management systems (LMS) in their classrooms. Usually, such a combination establishes a connection between one or more elements of one model (say CoI) and one or more elements of the other model (say UTAUT). In the study by Radovan and Kristl (2017), the connection point was the user behaviour in UTAUT connection teaching presence in CoI. Technology's actual use was determined by its frequency in teaching (teaching presence) within a blended learning environment.

The present study indirectly connects COI and UTAUT through student engagement. The premise for using engagement to connect UTAUT and CoI are:

- It is known that EdTech has the potential to improve student engagement (Norris & Coutas, 2014).
- A positive correlation has been observed between the utilisation of technology and student engagement, particularly during the initial phases of university education. (Chen et al., 2010).

- Because of technology, there are specific signs of more engagement, such as more interest and pleasure, better confidence and attitudes, and better interactions with peers and teachers (Bond et al.,2020).

The assumption is that students' engagement in the blended MOOC environment can be measured favourably by combining the CoI and UTAUT. Students use (from UTAUT 2) the blended MOOC environment for academic engagement (outcome from CoI). The result of combining CoI and UTAUT is Figure 4-2 as per the description in

Figure 4-1. Alraimi et al.'s (2015) research indicates a strong positive relationship between students' engagement and active participation in MOOCs and their satisfaction levels. According to this study, a positive correlation exists between students' utilisation and engagement with the content and interactive elements of a MOOC and their reported satisfaction with the learning experience. Bliuc et al. (2007) studied blended learning settings, which integrate online digital material with traditional classroom approaches. They discovered that this strategy improves student satisfaction. The flexibility, accessibility, and different learning modalities of mixed MOOC systems contribute to these attributes. A study by Margaryan et al. (2015) examined the academic performance of students enrolled in MOOCs and discovered that active engagement in course activities, such as discussions and completing assignments, was linked to improved performance results. Active participation in blended MOOC systems, rather than passive use, can significantly improve student performance. In their study, Zhao et al. (2005) discovered that students who engaged in blended learning, combining online and face-to-face components, often attained higher academic performance than those who exclusively depended on traditional classroom settings. This discovery emphasises the potential beneficial influence of blended MOOC systems on students' academic performance. From the discourse, this study makes the following hypothesis:
H18: Students' use (AU) and engagement (E) within the blended MOOC system will have a positive influence on their satisfaction (SS).
H19: Students' use (AU) and engagement (E) within the blended MOOC system will have a positive influence on their performance (AP).

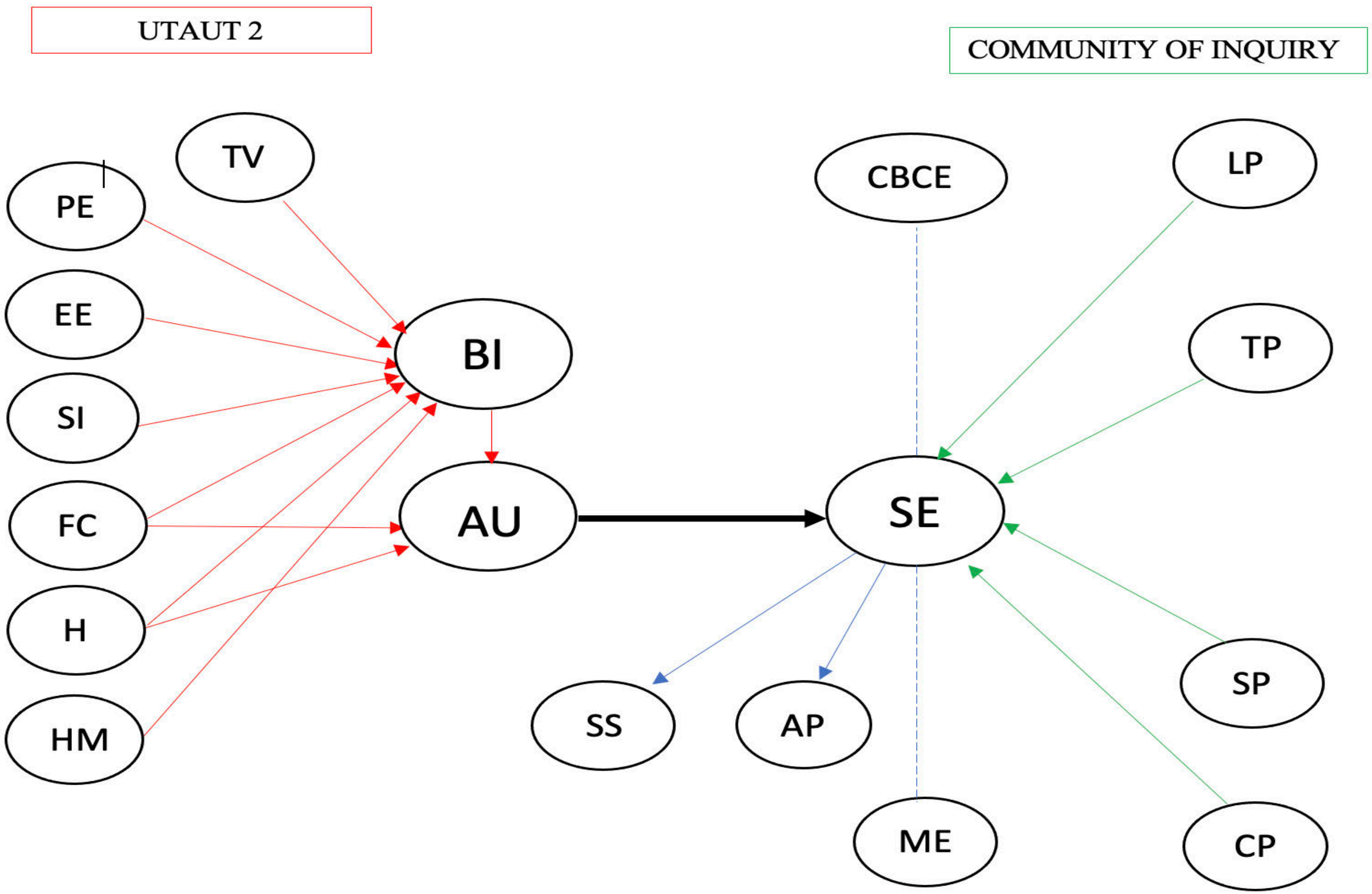

Figure 4-2.Research framework.

4.7 Summary

The chapter discussed theories that support the proposed conceptual framework shown in

Figure 4-1, which yields the research framework shown in Figure 4-2Figure 4-2. The significant parts of the framework were UTAUT 2 and CoI. The four presences of CoI were discussed along with their hypotheses, likewise that of the eight factors of UTAUT. Further discussions and hypotheses were made for students' engagement, satisfaction and perceived academic performance. Finally, a case was made for combining UTAUT and CoI via student engagement. Chapter 5 describes this study's research design and methods, directing data collecting and analysis.

CHAPTER 5: RESEARCH METHODOLOGY

5.1 Introduction

The chapter will evaluate the influence of students' acceptance and use of blended MOOCs on their engagement and its impact on their satisfaction and academic performance. The UTAUT 2 model examined students' actual use of blended MOOCs among others. In contrast, the COI model examined students' engagement with MOOCs. The chapter examines the impact of students' actual use of MOOC on their engagement with MOOC and its subsequent effect on their satisfaction with MOOC and academic performance. The intricate nature of this objective necessitates a meticulous consideration of the research methodology, the design of the study, the intended population, the sample and the process of sampling, the instrument for data collection, the challenges associated with data collection, the procedures for data processing and analysis, as well as the measurements of reliability and validity. This chapter is based on the following outline. Sections 6.2 and 6.3 examine the philosophical ideas the study is based on and explain why a postpositivist ontology and epistemology were selected. Section 6.4 discusses qualitative and quantitative research methods but focuses on why quantitative methods are better for this study. Section 6.5 discusses the different types of research done in the ICT field and explains why the survey method was used for this study. Section 6.6 describes the validity and reliability of the Instrument. Section 6.7 explains data processing and analysis. Section 6.8 deals with the Pilot study, Finally, section 6.9 highlights the ethical considerations with this study.

5.2 Research paradigm

There is "a basic set of beliefs that guide the action of conducting research", which according to Creswell and Creswell (2017), is known as a philosophical worldview, simply worldview or research paradigm. Research paradigms consist of epistemologies, ontologies, axiology and research methodologies or philosophies (p.44). These assumptions are the foundation of every research and describe the different basic ways of seeing the world and implementing the research. The basic philosophical assumptions that underpin human sciences or organisational-based research are ontology, epistemology, axiology (human nature, socio-cultural), and methodology (Burrell & Morgan, 1979; Wahyuni, 2012) and these account for differences in research paradigms.

Ontology deals with the nature of knowledge, the very essence of the phenomenon under investigation, or what exists in the world. From Creswell and Creswell (2017), ontology refers to how one perceives reality, which could be any of these two:

- Objectivist/ realist: Here, the reality exists independently of individual members of society and their own views. The subject that has to be researched is presented 'out there,' and it forces its way into the mind of the social actor from external sources.
- Subjective or nominalist: The reality in this view is dependent upon members of society and operates under the premise that everyone plays a role in shaping social phenomena. The subject is the product of a social actor's cognition or mind.

The relationship between social actors and reality (true) and how those actors "see" reality is what ontology investigates.

Epistemology is the study of the theories that explain how credible and valuable knowledge is made, analysed, and used(Creswell & Creswell, 2017). The crucial questions are how to share what is known and what can be known (Burrell & Morgan, 1979). There are two kinds of knowledge: one that is hard, real, and can be passed on concretely from one to the other, and another is soft, based on experience and insight, which must be experienced personally for the individual to gain such knowledge.

The study of ethics in research is known as axiology. It examines the function values play in research and the researcher's perspective on the research subject(Creswell & Creswell, 2017). The respect for and values of the research participants are also paramount here.

A set of guidelines for conducting research in accordance with a particular theory is known as a research methodology. The three different groups of assumptions will play a significant role in the conduct of the investigation. Methodology in research refers to the rules and methods employed to collect, sort out, and analyse data (Creswell & Creswell, 2017). It enables the researcher to provide detail and defend what was done and how it was done so that readers may judge the quality and merit of the research. The three sets of assumptions have direct implications for the methodology to be used for research. That is, the three assumptions (ontology, epistemology and axiology), when combined and concluded, yield a methodology (Burrell & Morgan, 1979, Usher, 1996).

The different categories of research worldview differ from authors, with examples of some grouping listed below.

- Constructivism or interpretivism, critical theory, positivism, and post-positivism (Guba & Lincoln, 1994).
- Critical inquiry, feminism, interpretivism, positivism, post-positivism and postmodernism (Crotty, 1998).
- Interpretivism (constructivism), positivism (naïve realism), post-positivism (critical realism), and pragmatism (Wahyuni, 2012).
- Critical realism, interpretivism, positivism, postmodernism and pragmatism (Saunders, Lewis, & Thornhill, 2016).
- Constructivism, post-positivism, pragmatism and transformation (Creswell & Creswell, 2017).

The nature of the world or reality one subscribes to will affect how one uncovers knowledge and social behaviour. Thus, an individual's choice of these research approaches depends on their beliefs and assumptions. A brief discussion of the research paradigm from the enumeration of Wahyuni (2012) is given in the paragraph, followed by a tabulation showing their differences in Figure 5-1. It is worth noting that positivism and interpretivism occupy two extreme research paradigms, *i.e.,* about the nature and sources of knowledge. For that matter, both positivism and interpretivism are mutually exclusive research paradigms.

The positivist perspective asserts that knowledge deemed reliable is limited to empirical observations, encompassing sensory experiences and measurable data. Positivists emphasise independence between the researcher and the individual or object being studied. Post-positivists say that the results are affected by the researcher's ideas, hypotheses, prior knowledge and values. Post-positivists aspire for objectivity by acknowledging biases' role in one's research. Positivists emphasise quantitative methods, whereas post-positivists also recognise the value of both quantitative and qualitative methods.

Depending on the specifics of the research subject, pragmatism studies incorporate both positivist and interpretivist perspectives. Therefore, the research question is essential for the pragmatist when deciding which research paradigm to embrace. In this regard, pragmatism can incorporate multiple research approaches and strategies within the same study. Moreover, in a study with a pragmatic approach, research methodologies such as qualitative, quantitative, and action may all be used in a single study using the proper research philosophy. The interpretivism accepts the subjectivist view that the meaning of the world is dependent on consciousness. That is, interpretivists interpret the elements of the study; bring human interest into the study. The research position of interpretivism is closely linked to philosophical inquiry, including social constructivism, phenomenology and hermeneutics.

	Research Paradigms			
Fundamental Beliefs	*Positivism (Naïve realism)*	*Postpositivism (Critical Realism)*	*Interpretivism (Constructivism)*	*Pragmatism*
Ontology: the position on the nature of reality	External, objective and independent of social actors	Objective. Exist independently of human thoughts and beliefs or knowledge of their existence, but is interpreted through social conditioning (critical realist)	Socially constructed, subjective, may change, multiple	External, multiple, view chosen to best achieve an answer to the research question
Epistemology: the view on what constitutes acceptable knowledge	Only observable phenomena can provide credible data, facts. Focus on causality and law-like generalisations, reducing phenomena to simplest elements	Only observable phenomena can provide credible data, facts. Focus on explaining within a context or contexts	Subjective meanings and social phenomena. Focus upon the details of situation, the reality behind these details, subjective meanings and motivating actions	Either or both observable phenomena and subjective meanings can provide acceptable knowledge dependent upon the research question. Focus on practical applied research, integrating different perspectives to help interpret the data
Axiology: the role of values in research and the researcher's stance	Value-free and etic Research is undertaken in a value-free way, the researcher is independent of the data and maintains an objective stance	Value-laden and etic Research is value laden; the researcher is biased by world views, cultural experiences and upbringing	Value-bond and emic Research is value bond, the researcher is part of what is being researched, cannot be separated and so will be subjective	Value-bond and etic-emic Values play a large role in interpreting the results, the researcher adopting both objective and subjective points of view
Research Methodology: the model behind the research process	Quantitative	Quantitative or qualitative	Qualitative	Quantitative and qualitative (mixed or multi-method design)

Figure 5-1.Fundamental Beliefs of Research Paradigms in Social Sciences

Source. **Wahyuni, 2012, p.70.**

5.3 Choosing Positivism for the Study

This research aligns with the positivist worldview based on its characteristics, as Creswell and Creswell (2017) outlined. The philosophical framework of positivism, derived from the works of Auguste Comte and endorsed by thinkers like John Stuart Mill, has profoundly influenced scientific investigation (Bryman, 2016; Guba & Lincoln, 2005). Several fundamental principles underpin it. Firstly, it affirms an independent reality that exists separately from the researcher's perspective. The objective nature of reality can be determined and measured using rigorous scientific methods, leading to factual information free from subjective biases. In addition, positivism emphasises using quantitative data collected through standardised instruments and subjected to statistical analysis to ensure objectivity and the potential for replicating the results (Bryman, 2016). In order to achieve unbiased results, it is necessary to employ established methodologies, minimise the impact of confounding variables, and conduct thorough data analysis (Cohen et al., 2007). Standardised tests and other empirical methods are considered to be more reliable than subjective assessments or personal experiences (Guba & Lincoln, 2005). The ultimate goal is to obtain results that can be generalised beyond the specific research context in order to uncover fundamental principles and consistent patterns that govern events (Punch, 2016). To summarise, positivism aims to discover universally applicable facts by employing objectivity, quantitative data, and statistical analysis (Bryman, 2016). Let us look at the justification for using positivist 'worldview for this study.

This study acknowledges the significance of pursuing objective and quantifiable knowledge under the positivist perspective. Although it can be difficult to achieve absolute truth, this study seeks to methodically examine the effects of blended MOOCs on student engagement, satisfaction, and performance. The study's methodology is based on the premise that through meticulous observation and quantification of the behaviours and experiences of students utilising blended MOOCs, empirical evidence can be established that enhances the comprehension of this phenomenon. This study recognises the intricacy of human behaviour, yet it endeavours to diminish this by conducting meticulous data collection and analysis. The primary instrument for data collection in this research is a questionnaire widely employed in quantitative studies. The study exclusively utilises a questionnaire as the sole instrument for data collection. The study constructed hypotheses that are objectively tested by following established frameworks such as UTAUT2 and CoI. The study posits that gathering quantitative data and conducting statistical analysis can reveal patterns and correlations that can yield valuable insights into the influence of blended MOOCs on education.

Positivists' research challenges reflect the necessity to separate and evaluate factors that ultimately impact outcomes. In this research, the outcomes of the conceptual framework are determined consecutively by the stated exogenous and endogenous factors. The method is a simplistic approach that aims to deconstruct intricate concepts into smaller components, which can be individually examined and tested, similar to the constituent elements of hypotheses and research questions. This study's conceptual framework can be divided into distinct components, each with its research questions and corresponding hypotheses.

a) The CoI framework's four presences shape the students' online experience by utilising blended MOOCs, as demonstrated in this study, along with their level of engagement.
b) The elements of the Unified Theory of Acceptance and Use of Technology (UTAUT) for blended MOOCs ascertain the inclination of students to utilise and their actual utilisation.
c) Both a) and b) positively affect students' satisfaction and academic performance. Nevertheless, this study integrated 1) and 2) to achieve the highest level of satisfaction and academic performance. Students' utilisation of blended MOOCs positively impacts their satisfaction and academic performance.

The positivist approach to knowledge construction is based on the empirical inquiry conducted through meticulous observation and measurement of the world. Empirical studies are necessary to disseminate this knowledge to the public and provide information for policymaking. Using the questionnaire ensures that the research findings are unbiased and impartial. Therefore, for a positivist, creating quantitative measurements of observations and examining human behaviour becomes highly significant. Phenomena are subject to laws or theories that require testing, verification, and refinement with factual evidence to comprehend things' functioning. The research utilises the extended UTUAT and revised COI frameworks, which are grounded in established theories. These constructs are distinct and can be used to predict the outcomes of students' online engagement, acceptance, and future use of technology. This study utilises the concepts of extended UTUAT and COI to assess the level of online participation among students in blended MOOCs. It also assesses their level of satisfaction with their participation and the perceived grades they hope to achieve in the learning environment. Ultimately, the study aims to ascertain the potential influence of incorporating blended MOOCs on students' engagement, satisfaction, and academic performance.

The positivist research approach adheres to the following sequence:

a) Commencing research with a theory.

b) Collecting data to either validate or challenge the theory.
c) Making essential modifications to the instrument if the initial outcome is unsatisfactory.
d) Conducting supplementary tests.

This research adheres to a precise sequence of activities to achieve the abovementioned goals. The proceedings suggest that the results of this research either support or challenge the findings of other studies conducted under similar conditions. Therefore, the research can be replicated, satisfying the criteria of the positivist approach. The input provided needs to be clarified or contain meaningful information.

Although acknowledging the potential for individual variation, this study focuses on identifying prevailing patterns and generalising findings applicable to a broader population. This study contributes to the existing knowledge in the field of blended MOOCs, thereby establishing a basis for making decisions based on evidence. This research aligns with the positivist worldview, focusing on empirical investigation, systematic data collection, and the quest for objective knowledge. The study offers valuable insights that can guide educational practices and policies.

5.4 Research Approach

The research approach is a crucial element of this study, functioning as the comprehensive strategy and methodology for gathering, analysing, and interpreting data per the study's objectives. This section will explore the research approach used, highlighting its alignment with a positivist philosophy. The research approach is intrinsically connected to the philosophical foundation of this subject, which is based on positivism. Positivism prioritises objectivity and relies on empirical observation, which makes it well-suited for quantitative research methodologies (Park et al., 2020). Quantitative approaches offer an impartial and unbiased evaluation of the phenomenon being studied, which is crucial for comprehending the complex connections inside the research issue. This study uses a quantitative methodology to investigate the relationships between variables related to the research problem. The study aims to examine and forecast the relationships between students' use of blended MOOCs, their engagement with the platform, and how it affects their satisfaction and perceived academic success. The researcher wants to produce definitive results that endorse, confirm, or validate these connections, adding to the current corpus of research on the influence of blended MOOCs. When using a quantitative approach to evaluate blended MOOCs, it is essential to acknowledge its limits. Quantitative analysis can reveal data trends and patterns but may not fully explain students' experiences. Quantitative surveys may not capture students' emotions, motivations, or contextual elements affecting blended MOOC perceptions. Thus, qualitative methods must supplement quantitative studies to comprehend students' subjective experiences and perspectives better.

The role of surveys is to gather data and information through a systematic and structured approach. In order to accomplish our research goals, the study utilises inquiry techniques that revolve around conducting surveys. Surveys are systematic tools for gathering data and providing statistical information crucial for predictive, explanatory, and confirmatory analysis (Maarouf, 2019). Survey instruments are very suitable for quantitative research since they facilitate data measurement and statistical analysis, enabling us to validate or refute alternative knowledge claims (Waardenburg et al., 2020).

Factorial Design is a research design that involves the manipulation of two or more independent variables, allowing for the examination of their individual and combined effects on the dependent variable (Baker et al., 2017). This research approach relies heavily on the use of a factorial design. This study employs a systematic analysis to investigate different categories of independent variables, such as the practical utilisation of blended MOOCs and students' level of engagement with them. We investigate the impact of these characteristics on outcomes such as student satisfaction and perceived academic performance in the classroom.

The factorial design is essential for studying the combined impacts of several factors on dependent variables (Baker et al., 2017). This design allows researchers to examine situations where students demonstrate different levels of engagement and utilisation. It explains the connections between these actions and their subsequent effects on satisfaction and academic performance.

The study utilises a deductive data analysis approach. This method entails generating hypotheses derived from established theories and subsequently devising research methodologies to empirically examine these ideas (Bingham & Witkowsky, 2021). Deductive methods integrate effortlessly with quantitative research and are suitable for hypothesis testing.

This study is solidly based on positivist ideology, which aligns with our research problem and objectives. The focus of positivism on objectivity and empirical observation aligns with the quantitative aspect of this research, which establishes a solid basis for the data gathering, analysis, and interpretation (Tjora, 2018).

5.5 Research Design

The study employed a cross-sectional research design to explore and understand the intricate relationships between students' utilisation of blended MOOCs, their engagement with the platform, and how these factors influence their overall satisfaction and perceived academic performance. It is essential to clarify that this research design does not encompass experimental intervention or the manipulation of independent variables; instead, it is centred on collecting and analysing observational data. A cross-sectional research design is particularly well-suited for acquiring insights into the existing state of affairs, investigating associations between variables, and discerning patterns at a specific point in time (Sekaran & Bougie, 2016). In this study, our primary objective was to examine the prevailing correlations between students' use of MOOCs, their levels of engagement, and their overall satisfaction and perceived academic performance within a specific timeframe.

The data collection process was executed through the administration of a comprehensive survey questionnaire to students across various academic levels within the University of X. This survey was thoughtfully constructed to capture crucial information regarding students' actual utilisation of blended MOOCs, their engagement levels with the platform, and their subjective assessments of satisfaction and academic performance. To ensure the clarity and effectiveness of the survey instrument, a five-point Likert scale measurement that allowed participants to express their responses accurately was implemented.

Advanced statistical tools were deployed further to explore the relationships and interdependencies between these critical variables. Specifically, the power of SPSS version 28 was used for the initial phase of descriptive statistical analysis, which primarily focused on assessing the normality of data distribution. This analysis was crucial for ensuring the integrity and reliability of the dataset, a vital step in any research endeavour (Hair Jr et al., 2011).

The choice of a cross-sectional research design for this study was motivated by its suitability for capturing a comprehensive snapshot of the relationships among the variables of interest as they existed at the time of data collection. It allowed us to investigate these relationships within a controlled setting and gather valuable insights into the contemporary state of MOOC utilisation, engagement, and student perceptions at the University of X.

5.5.1 Research Study Area

The geographical location of the study is crucial for future reference, replicability and validation of the study results. For this study, the study areas consisted of the students on the main campus of University X. Data collection, however, targeted students across different academic levels, including freshmen (level 100), sophomores (level 200), juniors (level 300), and postgraduates (level 800) at University X. The university is an institution that upholds the principle of equal opportunity and is well-positioned to provide a comprehensive education encompassing liberal arts and professional programmes. These programmes foster students' creativity, innovation, and moral responsibility. One of its colleges, the College of Distance Education, provides the know-how and facilities to educate business and education professionals. The university constantly seeks alternative ways to respond to changing needs. In order to meet the development demands of an ever-evolving global community, the university is continuously building on its current highly skilled professors and administrative personnel by providing a supportive atmosphere that encourages them to do so.

The University of Cape Coast (UCC) was founded in October 1962 with affiliation with the University of Ghana, located in Legon, a suburb of Accra. Per an Act of Parliament passed on October 1, 1971, the College was elevated to the status of a fully autonomous university with the right to award degrees, diplomas and certificates. Since there was a critical shortage of academically qualified teachers for the pre-tertiary level of education, UCC was founded to fill the need. Its original purpose was to train graduate professional teachers for second-cycle institutions and the Ministry of Education in Ghana to meet the needs of the accelerated education system there in terms of personnel. UCC has grown from 155 pioneer students' enrolment in 1963 to a current population of over 54,000 (Directorate of Public Affairs, 2022).

5.5.2 Population

The total student population, which is the target population as of 2022-2023 was 60,243 (see Table 5-1, comprising 54,236 undergraduate and 6,007 post-graduate students. However, the target population is 26,527 regular students.

Programme Type	Undergraduate	Postgraduate	Total

Regular	24,697	1,830	26,527
Sandwich	3,240	1,954	5,194
Distance	26,299	2,223	28,522
TOTAL	**54,236**	**6,007**	**60,243**

Table 5-1:2022 Student Population

Source. Directorate of Academic Affairs UCC (2022).

Furthermore, 25,239 students from Table 5-2 are the research population. Except for students from levels 50, 250, 850, 900 and 950, most of these students have completed ITS 101: Information Technology Skills course at UCC. This course is a semester course based on blended MOOC instructional delivery. ITS101 is a mandatory course for all level 100 students at UCC. Some 25,239 students have again completed additional blended MOOC courses at levels 200-800.

Table 5-2: 2022 Regular Students by Level

Level	Undergraduate	Postgraduate	Total
50	9		9
100	6051		6051
200	7204		7204
250	54		54
300	6197		6197
400	4931	N/A	4931
500	143		143
600	108		108
800		605	605
850		591	591
900	N/A	286	286
950		348	348
Total	**24,697**	**1,830**	**26,527**

Source. Directorate of Academic Affairs UCC (2022).

5.5.3 Sample and Sample Procedure

Sampling is choosing a smaller group of individuals or things from a larger population to reflect the population the researcher intends to examine accurately (Creswell and Creswell, 2017). The sample's representativeness was ensured using rigorous and standardised processes, which facilitated generalising the research findings. Cluster sampling was employed in this study to ensure a representative selection of students who have participated in the blended MOOC system.

Cluster sampling is a probabilistic method that divides a more significant population into smaller, more manageable groupings, known as "clusters," depending on specific characteristics like academic levels or courses. A subset of these clusters is chosen randomly to form the research sample (Creswell & Creswell, 2017). When researching large and widely spread populations, using probability sampling approaches such as cluster sampling is generally preferable. This approach has numerous benefits compared to essential random sampling:

- Representativeness: Cluster sampling guarantees that the sample accurately represents the total population.
- Efficiency: It surpasses purposive or non-random sampling approaches due to the researcher's exemption from individually identifying and selecting each participant.
- Reduced Bias: The sample is less prone to being distorted or biased due to the random selection of groups.

In order to establish the sample for this study, a compilation of blended MOOC classes available at University of Cape Coast(UCC) was acquired from the staff's mailing list. The population was categorised into academic or year levels (ranging from 100 to 800), except levels 50, 250, 850, 900, and 950, as these levels did not use blended MOOCs as an instructional format for any of their courses. The sample selection adhered to a two-stage cluster sampling methodology.

During the initial phase, academic levels (except any previously excluded) were chosen randomly from the strata using a lottery sampling technique. A distinct numerical value, commencing at 100, was allocated to each educational tier within the populace. The selection of academic levels for participation was conducted using random sampling, a simple probability sampling technique that necessitates only a basic understanding of the population. Random sampling is a method that ensures the accuracy and reliability of research results (Xiong et al., 2022). It guarantees that the findings from the sample closely reflect what would be achieved if the entire population were surveyed internally and externally. This approach ensures that each member of the population has an equitable opportunity to be chosen for the sample (Rahman et al., 2022) and can be implemented through a lottery or a random number generator. For the second phase, a further round of random selection was used to determine specific blended MOOC courses or classes within each designated academic level. Subsequently, all students registered in the selected courses were invited to partake in the study through the distribution of a Google Form questionnaire. Table 5-3 displays the chosen academic levels and class sizes of the blended MOOC courses at UCC. The students in question constituted the accessible population from which the final sample was selected.

Table 5-3: Level of students for the study

Level	**Total Number of Students**
100	3,051
200	250
300	180
800	25
Total	**3,506**

Source. Directorate of Academic Affairs UCC (2022).

The following occurred when the questionnaire was distributed as described:

1. Every student in the chosen course had an equal opportunity to be part of the sample, enhancing its representativeness.
2. The sample size was sufficiently large to obtain statistically significant results that could be generalised to the entire population.
3. Collecting data from a single course proved more efficient than gathering responses from multiple sources.

Past experience has indicated that response rates are higher when questionnaires are emailed to students. Additionally, it is a cost-effective and efficient online tool for swiftly collecting information (Fischer & Ghaffari, 2018). The underlying reason is that sending a fixed number of questionnaires to specific students cannot guarantee a 100% response rate, as some randomly selected students may not check their emails within the data collection period. Similarly, students may need to pay more attention to the questionnaire, potentially reducing the overall response rate and compromising data validity.

Hence, the study opted to broadcast the questionnaire to all students, expecting at least the specified number of students at each level to respond. This approach, akin to a census, aligns with the probability sampling method since no student could respond more than once, ensuring an unbiased selection process. Although more students responded than anticipated, the researcher could select the required sample size from the data for analysis or use the entirety of the responses to maximise variability. A similar approach was employed by Idarrou and Douzi (2020).

5.5.4 Data Collection Instruments

Data collection for this study was assisted by using a questionnaire, as described earlier. A questionnaire, as defined by Haseski and Ilic (2019), is a tool used in quantitative research to gather specific data on individuals' social surroundings or personalities. It functions as a vital instrument in guaranteeing the accuracy and dependability of data by methodically creating customised queries that target the specific areas being studied. In addition, questionnaires provide the advantage of using custom-designed scales to measure replies to the questions (Martínez-García et al., 2019).

The formulation of the questionnaire was a pivotal stage in this research undertaking. The questionnaires utilised in this study were developed by including content from two primary sources: pre-existing questionnaires and a comprehensive examination of the literature. The final questionnaire comprised eight sections, each focusing on different facets of the study inquiry. Hence, the questionnaire seemed quite broad as it aimed to address all areas of the research inquiries thoroughly. The ensuing paragraphs provide concise explanations for each of these sections.

The first section was made to get demographic details about the participants. The information collected are:

1) sex, which could be male or female.
2) generic academic programme grouping, which could be either STEM (Science, Technology, Engineering & Mathematics) or Non-STEM| Humanities (Business. Law, Arts and Social sciences).
3) The level at which the respondent last used blended MOOCs, i.e., 100 to 800.

The second part deals with the impact of the CoI model on students' engagement in blended MOOCs. As indicated in Chapter 5, the four presences used in the study are learning, cognitive, social and teaching. The constructs for each of the presences are listed as follows:

1) Learning presence has question items from these constructs: a) effort regulation, b) metacognitive self-regulation, c) motivation and d) self-efficacy for learning. Items from the Self-Efficacy scale were adopted from Shen et al. (2013), while the remaining items were adapted from Pintrich et al. (1991).
2) Cognitive presence has question items coming from these constructs: a) triggering event, b) explorations, c) integration, and d) resolution.
3) Social presence has question items that come from these constructs: a) affective expression, b) group cohesion and c) open communication.
4) Teaching presence has question items from these constructs: a) design & organisation, b) Facilitation, and c) direct instruction.

The third part deals with the blended MOOC engagement (BME) model adapted from Almutairi (2018) was used concerning students' engagement. The constructs for each of the factors of the blended MOOC engagement model are listed as follows:

1) Campus-based-course engagement has question items coming from these constructs: a) Collaborative Learning b) Higher-Order Learning, c) Learning Strategies, d) Reflective & Integrative Learning and e) Student-Staff Interaction.
2) MOOC Engagement has question items from these constructs: a) MOOC active learning, b) MOOC Social Interaction, and c) Teaching with MOOC.

The fifth part deals with the behavioural intention and actual use of blended MOOC, using UTAUT2. As indicated in Chapter 5, the factors used in the study are a) effort expectancy, b) facilitating conditions, c) habit, d) hedonic motivation, e) performance expectancy, f) social influence, g) task value, h) behavioural intention and i) actual use. The sixth part deals with satisfaction and performance obtained from blended MOOCs.

The adopted questions were rephrased to suit the target population. The students' responses were measured using a five-point Likert scale, with options ranging from 1 (strongly agree) to 5 (strongly disagree). According to Gooch and Vavreck (2019), using a questionnaire presents a cost-effective, expeditious, and effective means of acquiring substantial quantities of data from a broader geographic scope, mainly when conducting interviews is not feasible. Therefore, with so many students spread across a circuit of eleven schools, the questionnaire is the right instrument for data collection.

While certain scholars have acknowledged the existence of difficulties associated with employing questionnaires as a means of data collection, these challenges can be categorised as follows: a) the requirement of substantial expertise in order to develop a well-designed questionnaire, b) the potential for time-consuming data collection, c) the possibility of respondents selecting answers without fully comprehending the instructions and d) the task of processing the collected data for subsequent analysis (Covernton et al., 2019). There needs to be supporting evidence for these assertions raises doubts when addressing these critics (Hair Jr et al., 2021). However, other researchers like Xiong et al. (2022) have posited that the advantages of questionnaires in data collection are significantly more pronounced than their drawbacks. The prevalence of questionnaires across various research domains serves as substantiating evidence for this claim.

5.5.5 Data Collection Procedure

Data collection for this study was conducted by distributing a questionnaire to the designated participants. The research team distributed the questionnaire to all eligible students within the required groups, as indicated in Table 5-3, using a Google questionnaire form. The chosen technique was based on its practicality, as all students have institutional email addresses hosted on the Google platform, which made it easier to send out the poll. The original email invitation to students contained an introductory note that aimed to elucidate the study's goal and provide reassurance regarding the confidentiality of their responses. The letter underscored that the gathered data would be utilised solely for academic objectives and that involvement was optional. Students were urged to fill out the questionnaire during classroom sessions, and verbal prompts were given to emphasise the significance of their involvement. In order to achieve thorough coverage, bi-weekly reminder emails were dispatched to individuals who did not answer, commencing two weeks following the initial survey invitation. The poll remained accessible throughout the semester to accommodate participants' diverse schedules, and all responses were handled with rigorous confidentiality.

5.6 Validity and Reliability of the Instrument

Evaluating the soundness and dependability of the research tool is vital in guaranteeing the precision and resilience of the gathered data. In this context, validity refers to the degree to which the instrument accurately assesses the stated research aims and components (Daud et al., 2018). In order to accomplish this, the questionnaire underwent a thorough examination process to verify its appropriateness for the study.

The research instrument was initially derived from existing studies and subsequently tailored to suit the unique study setting and target audience. In order to improve its credibility, the questionnaire underwent a thorough evaluation by the study's supervisor, who contributed professional insights and recommendations. In addition, a thorough literature study was performed to guarantee that the items in the questionnaire were unambiguous, precise, captivating, and pertinent to the research goals.

A sequence of statistical tests was conducted to assess the instrument's dependability. The Cronbach's Alpha test, with a minimum threshold of 0.7, was utilised to evaluate the internal consistency (Tavakol & Dennick, 2011). The objective of this test was to assess the degree of internal consistency in measuring the same concept throughout the questionnaire's components. Additionally, an analysis of variance (ANOVA) was performed to evaluate the statistical significance of differences within and between the questionnaire items.

A factor analysis was conducted to verify the questionnaire's ability to measure certain constructs accurately. This research evaluated how the items accurately measured the intended concepts and whether they exhibited meaningful response patterns (Bandalos, 2018). In addition, Bartlett's test of sphericity was used to assess the correlation between variables, determining their appropriateness for structural analysis. A significance level below 0.05 suggests that factor analysis suits the collected data.

The adequacy of the sampling was assessed using the sampling adequacy index, with a recommended threshold of 0.6. Additionally, Bartlett's test of sphericity was predicted to have a value below 0.05, which further confirmed the appropriateness of doing factor analysis (Bhuiyan & Gani, 2015). Ultimately, to obtain a wide range of comments and guarantee the questionnaire's efficacy, participants were encouraged to provide their overall evaluations of the survey, emphasising its clarity, delivery, engagement, and accuracy. This comprehensive method aimed to develop a streamlined and productive questionnaire for data gathering (Hair Jr et al., 2021).

The subsequent sections of this chapter will provide comprehensive explanations of the statistical tests employed and their corresponding results, offering a comprehensive evaluation of the questionnaire's validity and reliability.

5.7 Data Processing and Analysis

In this research phase, the collected data underwent a series of rigorous processes and analyses, leveraging specific statistical techniques and tools. These procedures were essential to transform the raw data into valuable insights that would effectively address each research question, as Odenkirk et al. (2021) expounded upon. Following the completion of the data collection phase, meticulous scrutiny and data cleaning were conducted to ensure that all responses adhered to the prescribed instructions. Each response was assigned a numerical code corresponding to its respective research question. These coded responses were then entered into the IBM SPSS Statistics 28.0 for mac.

To ensure data integrity, a missing values analysis was performed to identify and address any missing data points that could compromise the analysis's validity. Subsequently, a descriptive analysis was employed to evaluate the normality of data distribution. This step was crucial in determining whether a parametric or non-parametric analysis approach should be adopted based on the skewness of the data.

The research model encompassed four distinct research questions. The data was transformed into a comma-separated values (CSV) file to analyse this model effectively and imported into SmartPLS 4 software for a Partial Least Squares (PLS) regression analysis. The chosen approach in this study involved two key steps. Firstly, many variables were condensed into a reduced set of components to enhance manageability and reduce complexity. Subsequently, rather than conducting a traditional least-squares regression analysis on the original data, the analysis was performed on these condensed components, streamlining the process and improving efficiency (Mura et al., 2020).

The PLS algorithm, akin to principal components analysis, was employed to effectively reduce the number of variables. This reduction was achieved by extracting components that encapsulated the strongest correlations among the determinants (Hair et al., 2019). The methodology employed in this study entailed utilising various components as variables, with cross-validation, to determine the smaller components that exhibited the highest predictive capability (Helland et al., 2018).

Consequently, the data concerning students' actual usage of blended MOOCs and their engagement with these platforms (exogenous variables) were regressed against data related to their satisfaction and perceived academic performance (endogenous variables). The application of the PLS algorithm unveiled the extent to which students' actual use of MOOCs and their engagement influenced their satisfaction and academic performance.

5.8 Pilot Test

Before the main study, a pilot study was conducted to ascertain the validity and reliability of the research instrument and its suitability for the main study. The pilot test results are an outcome of assessing the research instrument's validity and reliability. The researcher did the pilot test at the University of X for a final assessment of how the data collected from the instrument will fit the model. The goal was to examine the construct reliability and validity, the discriminant validity and the model fit. These measurements are the quality criteria that better assess the accuracy, validity, uniqueness, completeness, consistency, integrity and conformity of the research instrument.

5.8.1 Demographic characteristics

The demographic characteristics of the pilot study participants are aggregated in Table 5-4Table 5-4.

Table 5-4:Demographic characteristics of pilot participants

		Frequency	Percentage
Sex	Female	51	46.8
	Male	58	53.2
	Total	**109**	**100.0**
Programme	STEM (Science |Technology | Engineering & Mathematics)	76	69.7
	Non-STEM (Business | Law | Arts and Social Sciences | Humanities)	33	30.3
	Total	**109**	**100.0**
Level	100	55	50.5
	200	13	11.9
	300	29	26.6
	800	12	11.0

	Total	**109**	**100.0**

Source. Pilot test, 2022

Table 5-4 summarises sample sex, programme, and level. It can assist in understanding the sample composition and how it may affect outcomes. In all, 109 students, 58 males and 51 females, participated in the pilot study. More males, STEM and level 100 students participated in the pilot study. The data obtained from the pilot study were further analysed to check for the instrument's reliability and whether the dataset fits structural equation modelling.

5.8.2 Internal consistency reliability

Internal consistency, an essential component of assessing dependability, measures the extent to which items that measure the same construct are interconnected. It investigates the presence of a coherent connection between the scores of various items intended to measure a particular concept. The evaluation of internal consistency is commonly known as Cronbach's alpha or internal reliability (Ravinder & Saraswathi, 2020).

Cronbach's alpha (α) is a commonly used metric for evaluating the internal consistency of each concept in a research model (Hair Jr et al., 2021). This coefficient is especially useful when numerous questions assess the same underlying notion. Internal consistency refers to how a set of questions accurately measures a particular concept or latent variable (Hair Jr et al., 2021). It is important to emphasise that although a high alpha value may imply excellent reliability, it does not exclusively reflect unidimensionality. Unidimensionality denotes that all items within the scale assess the identical factor. Nevertheless, obtaining a substantial alpha value when assessing multiple factors or dimensions is feasible, provided that the items exhibit sufficient interrelationships. Therefore, a high alpha value by itself is insufficient to establish the unidimensionality of a measure. The alpha value is determined by various criteria, including the quantity of indicator items, their similarity, and the number of dimensions they represent. Optimally, the findings of Cronbach's alpha should lie between 0 and 1. However, negative values may indicate data-related problems, such as errors in data input (Tavakol & Dennick, 2011).

From Tavakol and Dennick (2011), cronbach's alpha coefficient higher than 0.70 is regarded as a reliable measure of internal solid consistency. Values greater than 0.80 are highly desirable, while values between 0.90 and 0.95 are considered excellent. However, values above

0.95 may raise concerns (Vaske et al., 2017; Yaghoubi Farani et al., 2019). It is essential to mention that alpha values ranging from 0.65 to 0.80, indicated as $0.65 \leq \alpha \leq 0.80$, are generally considered satisfactory (Tavakol & Dennick, 2011).

The Cronbach's alpha coefficients calculated for each construct in Table 5-5 exceeded the minimum threshold of 0.722, suggesting excellent internal consistency and confirming that the items are appropriate for their respective constructs. An anomaly was detected in the Motivation sub-construct of the Learning presence construct, resulting in an alpha value of 0.66.

Table 5-5:Outer Loadings and Cronbach's alpha for each construct

Construct	Items	Outer Loadings	Cronbach's alpha
Perceived Academic Performance (AP)	AP1	0.730	0.852
	AP2	0.840	
	AP3	0.789	
	AP4	0.811	
	AP5	0.790	
Actual Use (AU)	AU3	0.800	0.831
	AU4	0.802	
	AU5	0.860	
	AU6	0.795	
Behavioural Intention (BI)	BI4	0.851	0.852
	BI5	0.876	
	BI7	0.897	
CP (Exploration)	CPE1	0.950	0.896
	CPE2	0.830	
	CPE3	0.949	
CP (Integration)	CPI1	0.867	0.812
	CPI2	0.849	
	CPI3	0.841	
CP (Resolution)	CPR1	0.838	0.760
	CPR2	0.888	

	CPR3	0.736	
CP (Triggering Event)	CPTE1	0.856	0.810
	CPTE2	0.864	
	CPTE3	0.834	
Effort Expectancy (EE)	EE1	0.788	0.830
	EE2	0.797	
	EE4	0.876	
	EE5	0.790	
Facilitating Conditions (FC)	FC1	0.799	0.877
	FC2	0.799	
	FC4	0.800	
	FC5	0.859	
	FC6	0.834	
Habit(H)	H1	0.867	0.856
	H2	0.866	
	H3	0.908	
Hedonic Motivation (HM)	HM1	0.887	0.823
	HM2	0.821	
	HM3	0.865	
LP (Effort Regulation)	LPER2	0.809	0.790
	LPER3	0.870	
	LPER4	0.838	
LP (Motivation)	LPM2	0.763	0.660
	LPM3	0.780	
	LPM6	0.768	
LP (Metacognition Self-Regulation)	LPMSR1	0.766	0.769
	LPMSR2	0.836	
	LPMSR3	0.878	
LP (Self-Efficacy for Learning)	LPSEL1	0.805	0.721
	LPSEL2	0.803	
	LPSEL4	0.796	
Performance Expectancy (PE)	PE1	0.752	0.880

	PE2	0.748	
	PE3	0.840	
	PE4	0.857	
	PE5	0.904	
Student Engagement (SE)	SE1	0.774	0.895
	SE12	0.719	
	SE15	0.724	
	SE17	0.714	
	SE19	0.724	
	SE23	0.728	
	SE25	0.772	
	SE4	0.721	
	SE7	0.753	
Social Influence (SI)	SI1	0.831	0.896
	SI2	0.818	
	SI3	0.721	
	SI4	0.788	
	SI5	0.809	
	SI6	0.725	
	SI8	0.766	
SP(Affective Expression)	SPAE1	0.807	0.742
	SPAE2	0.751	
	SPAE3	0.877	
SP(Group Cohesion)	SPGC1	0.891	0.749
	SPGC2	0.737	
	SPGC3	0.819	
SP (Open Communication)	SPOC1	0.737	0.742
	SPOC2	0.819	
	SPOC3	0.890	
Students' Satisfaction (SS)	SS1	0.758	0.872
	SS2	0.767	
	SS3	0.798	

	SS4	0.777	
	SS5	0.829	
	SS6	0.755	
TP(Direct Instruction)	TPDI1	0.851	0.760
	TPDI2	0.870	
	TPDI3	0.730	
TP (Design and Organisation)	TPDO1	0.821	0.838
	TPDO2	0.844	
	TPDO3	0.838	
	TPDO4	0.779	
TP(Facilitation)	TPF1	0.865	0.908
	TPF2	0.867	
	TPF3	0.721	
	TPF4	0.858	
	TPF5	0.872	
	TPF6	0.781	
Educational Task Value (TV)	TV1	0.765	0.858
	TV2	0.714	
	TV3	0.816	
	TV4	0.819	
	TV5	0.711	
	TV6	0.758	

Source. Pilot test, 2022

Note: CP, LP, SP and TP, respectively, stand for cognitive presence, learning presence, social presence and teaching presence.

5.9 Multivariate distribution

The assumption that a multivariate distribution is normally distributed is what the term "multivariate normality" means Kline (2011). From Kline (2011), six criteria must be met for a multivariate distribution to be classified as multivariate normal are:

- Linearity: Any two variables in the distribution must have a linear connection.

- Marginal Normality: All variables have a normal distribution.
- Independence: Distribution factors must be unrelated or the lack of multicollinearity

A multivariate distribution is considered multivariate normal if and only if it meets the six criteria (Kline, 2011). Nevertheless, if one of these rules is broken, they cannot call the distribution multivariate normal. Any deviation from these conditionalities disqualifies the distribution as multivariate normal. The normal distribution must be assumed to perform certain statistical analyses or use a structural equation model (Hair Jr et al., 2010). Hair et al. (2010) define normality as the degree to which data distribution for a given measure variable matches the standard normal distribution.

Structural equation modelling uses hypothesis tests and parameter estimates to infer causality within a conceptual model. The results are reliable if the data meet all the assumptions an estimation method requires (Gao et al., 2008). In SEM, whether the sample has a multivariate normal distribution or not affects which estimation method will be used and how reliable the most common estimates are going to be. However, real-world data rarely have normal distributions (Gao et al., 2008). Applying a normal theory-based estimation method to a multivariate non-normal sample is necessary. Before using SmartPLS to do an SEM study, ensuring that the data fit the SEM assumptions is essential. Normality, linearity and the lack of multicollinearity are some of these assumptions. Researchers may transform raw data or delete "outliers" to bring a sample closer to compliance (Gao et al., 2008).

Hair et al. (2013) define normality as the distribution of data for each metric variable and how well it fits the statistical standard normal distribution. When working with Likert scale data, the appropriate normality test depends on the number of response options and the sample size. There are no clear rules about how significant skew or kurtosis values must be to show that the data are non-normal (Simon, 2018). Streiner and Norman (1995) say that there is a problem if 80% or more of people answer at one end of the scale; otherwise, it does not matter. A multivariate normal distribution implies that each variable within a given sample follows a univariate normal distribution. In contrast, each combination of variables exhibits a bivariate normal distribution. In contrasting univariate and multivariate normal distribution Gao et al. (2008) said the following:

- Multivariate normality shows how the group is distributed, while univariate normality shows how one variable is distributed.
- The single normal distribution for each measure is needed for the multivariate normal distribution.

- When each variable has its non-normal distribution, it is generally a multivariate non-normal distribution.

Univariate and multivariate skewness and kurtosis Likert items are often treated as normal in the literature (Cain et al., 2017). When a distribution's left and right sides are different in that they are not mirror images of each other, it is considered asymmetrical (uneven). Skewness and kurtosis are also easy ways to understand the normality of distribution (Cain et al., 2017).

5.9.1 Skewness and Kurtoses

Skewness can be right (positive), left (negative) or no skewness (zero) for a distribution. A skewness number between -1 and 1 usually means that the two sides are about the same. If the skewness number is outside of this range, it means that the skewness is moderate to high. Larger absolute values mean that the skewness is stronger. Kurtosis compares a distribution's "peakedness", "peakness" or "flatness" to a normal distribution. A normal distribution has a kurtosis of 0. Leptokurtic distributions have positive kurtosis greater than 0, making them more peaked (peaker) than normal distributions. Whereas platykurtic distributions have negative kurtosis of less than 0, making them more flattened (flatter) than a normal distribution. A kurtosis number of 3 implies the distribution has the same kurtosis as a normal distribution. (i.e., a mesokurtic distribution). When the kurtosis value is greater than 3, the tails are heavier, and the peaks are sharper. (i.e., leptokurtic distributions). Less kurtosis is shown by values less than 3, and smaller values show flatter tails and bigger peaks. (i.e., platykurtic distributions). Leptokurtic and platykurtic data affect statistical accuracy (Schumacker & Lomax, 2004, as cited in Mîndrilă, 2010). Figure 5-2 shows the various types of kurtoses and skewness.

The skewness and kurtosis test were used to ensure normalcy in this research (Tabachnick & Fidell, 2013). However, when the sample size exceeds 200, Tabachnick and Fidell (2013) note that the departure from the normality of skewness and kurtosis typically does not significantly alter the analysis. In the opinion of Oppong and Agbedra (2016), it is commonly assumed that the data follows a normal distribution for large samples, regardless of the underlying distribution. Bryne (2010) and Hair et al. (2010) argue that the data can be called normal if the skewness is between -2 and +2 and the kurtosis is between -7 and +7. Cain et al. (2017) extended further by emphasised that skewness and kurtosis remain between ±3 and ±10, respectively. However, Curran et al., 1996 hinted that thresholds of 2.0 for skewness and 7.0 for kurtosis are moderate normality. Furthermore, Kline (2015) suggested that a skewness or kurtosis with an absolute value of more than 3 or 10, respectively, may indicate a problem and an absolute value of more than 20 may indicate a more severe problem. Therefore, this study sticks to the recommendation that skewness and kurtosis should not exceed 3 and 10, respectively, in absolute value.

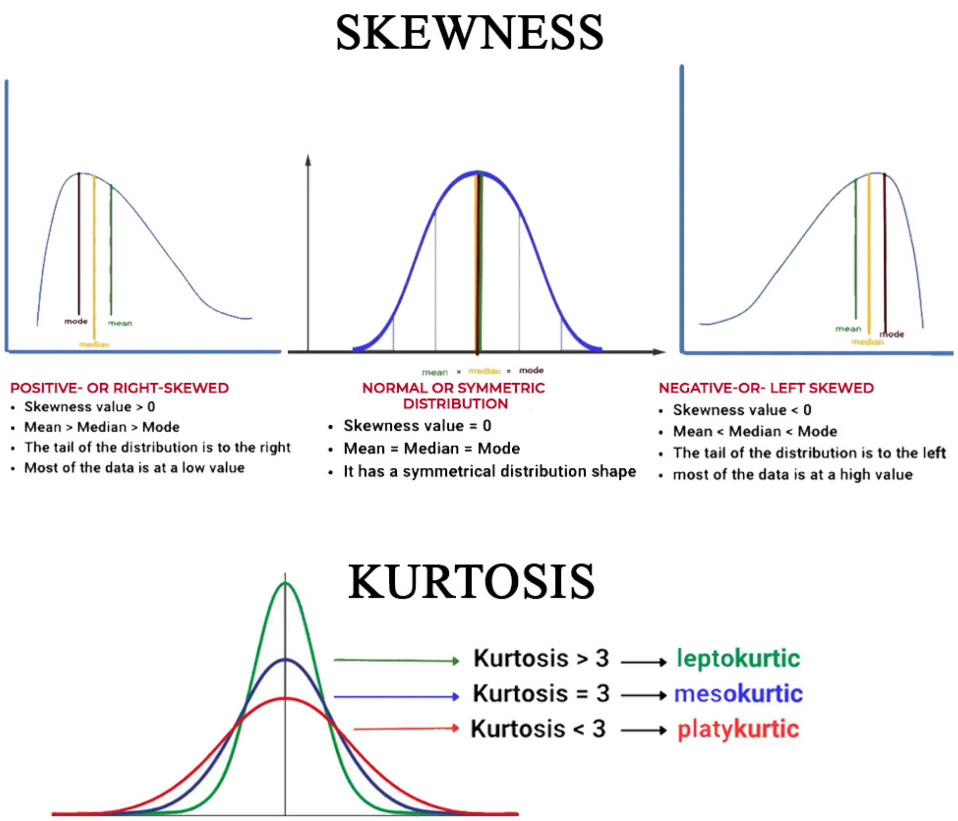

Figure 5-2.The various types of Skewness and Kurtoses

5.9.2 Univariate skewness and kurtoses individual constructs

From DeCarlo's (1997, as cited in Cain et al., 2017) assertion, if skewness is not 0, the distribution is not symmetrical. If kurtosis is not equal to 0, the tail mass and shoulder of a univariate (single) data set does not follow the normal curve. Thus, the presence of non-normality can be verified by examining skewness and kurtosis values (Mîndrilă, 2010). This study checked normality with skewness and kurtosis (Tabachnick & Fidell, 2013). Tabachnick and Fidell (2013) further asserted that when the sample size is over 200, non-normal skewness and kurtosis often do not matter.

5.9.3 Multivariate skewness and kurtosis for all constructs

The evaluation of multivariate normality is commonly expected when conducting an SEM. The maximum likelihood estimator employed in SEM relies on the underlying assumption of multivariate normality. However, researchers frequently encounter situations where their data violates this assumption and must possess a sufficiently large sample size to employ distribution-free estimation methods (Nevitt & Hancock, 2001). In practical scenarios, it is common to encounter model misfit and non-normal data (Lai, 2018). In SEM, Mardia's coefficient consistently demonstrates statistical significance when the expected sample size is substantial. The utilisation of Mardia's multivariate skewness and kurtosis coefficients is frequently observed in SEM methodologies (Gao et al., 2008). Mardia's coefficient tests the notion of normality in multivariate data, using multivariate skewness and kurtosis. Nevertheless, it is essential to note that determining a definitive threshold for Mardia's multivariate skewness and kurtosis coefficient lacks consensus. The interpretation of what is deemed "reasonable" or "acceptable" is contingent upon the specific research inquiry and the characteristics of the data under examination. Nevertheless, in the literature, some broad rules have been put forward. Kline (2011) indicates that values of Mardia's coefficient greater than 3.0 show significant multivariate non-normality, while values between 1.0 and 3.0 indicate some non-normality but may be acceptable depending on the sample size. Values below 1.0 mean that the multivariate distribution is normal.

5.10 Ethical Considerations

It is highly recommended that research worthy of reading and implementation must be done in a way that does not break ethical rules. Kjellstrom et al. (2010) looked at the PhD dissertations of 64 Swedish nurses and found these seven ethics themes they covered. Based on their respective frequencies of occurrence, the identified themes about ethics encompassed the following aspects: 1)the acquisition of ethical approval, 2) the provision of comprehensive information and obtaining informed consent, 3) the maintenance of confidentiality, 4) the consideration of ethical dimensions in research methodologies, 5) adherence to ethical principles and regulations, and 6) the rationale behind conducting the study and the equitable selection of participants. The right ethical considerations for this study were made in line with generally accepted standards for study ethics. As suggested by (Arifin, 2018; Kjellstrom et al., 2010; Krug et al., 2011), the main ethical considerations highlighted in this study are discussed in the following paragraphs.

1. Anonymity: The researcher ensured the subjects' answers were anonymous (Krug et al., 2011). This aspect was done by ensuring that the questionnaires did not ask for any identifying information from the people who filled them out and by combining the study data so that individual participant responses could not be traced back to them. This aspect is essential, and students were asked what they thought about how well they did in school because of blended MOOCs.
2. Confidentiality and the right to privacy: The researcher made sure that no one knew who the subjects were (Krug et al., 2011). Though the researcher did not cover this aspect in the present study, it can be done using fictitious names or codes instead of real ones.
3. Informed consent. All students who took part in the study were given an informed consent form that explained the study's goal, what was expected of them, and that they could leave the study at any time if they did not want to. As part of this theme, Krug et al. (2011) included the data collection methods and how the data will be used. A copy of the consent form is annexed to the dissertation. Approval was also sought from the gatekeeper from UCC before the students were polled. Both were on the paper that the students had to read.
4. Protecting, storing and deleting research data: The data were handled per the university ethics committee's request that it be kept in a safe place with the supervisor for at least five years. After that, the data were erased from all storage devices. However, the data can only be made available to authorised university employees.
5. Sharing data: The data can be given to other researchers if they ask, which helps with transparency and responsibility (Bergdahl et al., 2020). Nevertheless, this part will be done once the participants have given their informed consent, their names have been protected, and the university's authority has approved.
6. Analysis of the facts without bias: The experts, like the supervisor, ensured that the study was conducted fairly and objectively. This aspect was done by making the study so that any possible biases are kept to a minimum and by looking at the data in a way that does not rely on assumptions or preconceptions.
7. Ethical Board's approval. Above all the issues raised, the college and university ethics committees also carefully examined the study. This aspect was the pre-condition before starting the research. Again, ethics boards/committees are made up of experts in judging

the ethical matters of research. Thus, the Board ensured that the study met ethical standards and did not harm the participants (Shaw, 2010).

5.11 Summary

Chapter 5 is a pivotal segment of the thesis, encompassing various critical research design and methodology aspects. The chapter begins by elucidating the rationale behind the selection of positivism as the preferred research paradigm, offering a robust justification for its alignment with the quantitative nature of the study. Within the realm of research design, this chapter meticulously delves into essential components, including the delineation of the study area, the definition of the target population, the intricacies of sample selection, the choice of data collection instruments, and the methodology governing data collection. Notably, cluster sampling and random selection are expounded upon, focusing on their advantages, mainly when dealing with extensive, geographically dispersed populations. The chapter underscores the potency of questionnaires as primary data collection devices, especially when gathering information from a diverse and widely scattered student population. It further emphasises the significance of ensuring the validity and reliability of these instruments, elucidating the meticulous steps taken to guarantee their effectiveness. The data processing and analysis section unveils the practical intricacies of transforming raw data into meaningful insights. Here, the rationale for employing SmartPLS to assess internal consistency reliability, utilising Cronbach's alpha, is outlined. This meticulous approach ensures the reliability and consistency of the research instrument, enhancing the study's trustworthiness. Ethical considerations, a cornerstone of responsible research, receive meticulous attention in this chapter. The discussion encompasses a comprehensive ethical framework, encompassing anonymity, informed consent, secure data handling, and the imperative role of ethical board approval. These ethical principles underscore the commitment to conducting research that upholds the highest ethical standards, safeguarding the rights and privacy of research participants.

In essence, Chapter 5 lays the groundwork for the entire research endeavour. It aligns the chosen research paradigm with the study's quantitative nature, elucidates the intricacies of research design, underscores the significance of robust data collection instruments, ensures data validity and reliability, and upholds unwavering ethical standards. This chapter serves as the bedrock upon which the subsequent phases of the study are built, ensuring the research's rigour, integrity, and ethical soundness. Chapter 6 will present data analysis and explain the outcomes, providing data insights

CHAPTER 6: DATA ANALYSIS AND DISCUSSION OF RESULTS

6.1 Introduction

This chapter aims to measure, describe and summarise data logically with tables and graphs. The chapter presents an overview of the response rate and participants in Sections 6.2 and Sections 6.3. Section 6.4 discusses the data distribution with descriptive statistics. Section 6.5 offers the normality test of the data collected, using univariate and multivariate skewness and Kurtosis. Section 6.6 deals with the Histogram with KMO and Bartlett's test of sphericity discussed in section 6.7. The chapter is summarised in Section 6.8.

6.2 Response Rate

The average response rate for research surveys is very different depending on the type of survey and the audience being surveyed. A meta-analysis of online surveys from different fields showed an average response rate of 39.6% with standard deviation of 19.6% (Wu et al., 2022). The statement means that, on average, 39.6% of the people asked to participate in these online surveys did so. The standard deviation (SD) of 19.6% shows that the response rates to online surveys differed from one study to the next, running from as low as 20% to as high as 60% in some cases. Saunders (2014) also said that a response rate of around 30% in a random group is considered good. As indicated in Table 6-4, the researcher sent the questionnaire to all the 3,506 students identified in the accessible population. A link to the same questionnaire was added on the Moodle LMS pages of courses that use blended MOOCs as a way to teach. This mailing list comprises 3,506 students who have used blended MOOCs at UCC for at least one semester. However, of the 3138 that completed the questionnaire, 2875 students filled it out successfully without missing data. The response rate was 82%, which is adequate for the study.

6.3 Participants

From this point forward in this study, the words participants, respondents or students will be used interchangeably. Most respondents indicated that they participated in blended MOOCs as the first-year University of X students (Level 100). They enrolled on the Alison MOOC platform for Microsoft Office 2010 -Revised 2018 as OER for a campus-based course entitled ITS 101, which is a mandatory for all level 100 students. They watched the videos on the platform, participated in both the discussion forums and answered the quizzes to obtain a certificate. The marks on their certificate became part of their continuous assessment for the campus course they enrolled in. The continued students at the upper levels enrolled unto other MOOC platforms like Coursera and Saylor just like the Alison.

6.4 Data Descriptive Analysis

The descriptive statistics are shown in Tables 6.1 to 6.5.

Table 6-1:Demographic data of respondents

Parameters	Categories	N	%
Sex	Female	1,041	36.20
	Male	1,834	63.80
	Total	**2,875**	**100**
	STEM—Science, Technology, Engineering & Mathematics	1,875	65.20
	Total	**2,875**	**100**
Level			
	100	2,442	84.90
	200	241	8.40
	300	156	5.40
	800	36	1.30
	Total	**2,875**	**100**

Source: Fieldwork 2022

Table 6-1 shows an overview of the demographic data of the respondents. EdTech research depends on these bio-demographic data, which is crucial for designing, implementing and evaluating technology interventions. They could help find subpopulations that need more complicated and subtle treatments, eliminate confusing factors and make policy decisions about how to use technology in the classroom.

In a blended MOOC study, including demographic data, like sex, may assist researchers in determining whether sex-related issues affect learning. This information helps to ensure that instructional technology is sex-neutral and easy to use. Studies suggest sex inequalities in educational technology usage and acceptance. Several studies suggest that males are more tech-savvy than women (Irene, 2019). In Table 6-1, it is evident that most respondents were male, mirroring the predominant gender composition of the University of Cape Coast(UCC) student population.

In educational research, sorting is often used to tell the difference in perception and use of EdTech between students in STEM programmes and those who are not. The grouping is based on the idea that STEM and non-STEM students have different educational needs and experiences. Lin et al. (2021) reported that the factors affecting students' intentions to continue using the platforms differed between STEM and non-STEM courses, with perceived usefulness being more important in STEM courses and perceived ease of use being more critical in non-STEM courses. Another study by Alkhalaf and Nguyen (2020) also showed that EdTech positively affects student learning outcomes in STEM and non-STEM courses. However, the effect was more significant in STEM courses than in non-STEM. Table 6-1, reveals a higher participation of STEM students in the survey, which aligns with the university's greater representation of STEM colleges.

It is essential to consider the academic year of the respondents when analysing the data on satisfaction, academic performance and other variables related to blended MOOCs, as it may impact their experiences and perceptions of the technology. Additionally, understanding how experience with blended MOOCs varies by academic year can inform future design and implementation of such technologies. Based on the data, the majority of the respondents (85%) enrolled in blended MOOCs at level 100, indicating that they were in their first year of study when they enrolled. This result suggests that most respondents were relatively new to blended MOOCs and may have needed more experience with them than more advanced students. Additionally, the limited number of respondents at higher levels (300, 500, and 800) implies that blended MOOCs may be less commonly used or required in the later stages of their academic journey. This comprehensive demographic data analysis serves as a foundational framework for understanding the respondent population's characteristics, which can significantly influence the outcomes and implications of the study.

Table 6-2 displays the aggregations of the Likert responses of the question items from the four presences (12, 13, 12 and 24 items, respectively, for TP, SP, CP and LP).

Table 6-2:Responses from the four presences of the community of inquiry

Factors	**Response categories**	**Responses**	
		N	**%**
Teaching Presence	Strongly disagree	11	0.4
M=4.47, SD= 0.648	Disagree	18	0.6
Mode = 5	Undecided	125	4.3
	Agree	1,180	41.0
	Strongly agree	1,541	53.6
	Total	**2,875**	**100**
Social Presence	Strongly disagree	12	0.4
M=4.38, SD= 0.710	Disagree	40	1.4
Mode = 5	Undecided	192	6.7
	Agree	1,221	42.5
	Strongly agree	1,410	49.0
	Total	**2,875**	**100**
Cognitive Presence	Strongly disagree	9	0.3
M= 4.46, SD= 0.650	Disagree	23	0.8
Mode = 5	Undecided	128	4.5
	Agree	1,204	41.9
	Strongly agree	1,511	52.6
	Total	**2,875**	**100**
Learning Presence	Strongly disagree	6	0.2
M= 4.47, SD=0.621	Disagree	15	0.5
Mode = 5	Undecided	119	4.2
	Agree	1,169	41.4
	Strongly agree	1,516	53.7
	Total	**2,875**	**100**

Source: Fieldwork 2022

Teaching presence is integral to a blended MOOC that helps students learn well. The results for teacher presence show that about 94.6% (53.6 + 41.0) of the students thought the teaching in the blended MOOC system was good. This result fits well with other results that showed students agreed with the questions about the teaching presence's constructs. (McKerlich, et al., 2011). This result shows that most students feel the same about the teaching presence. The fact that students were active in the blended MOOC setting shows that they were interested. A teacher's presence is critical in getting students interested and satisfied in online and blended learning settings (Garrison & Anderson, 2003; Richardson & Swan, 2003; Wang et al., 2011). Students felt like their teachers were interested in the course and made them feel like they were there. The fact that many students liked the teaching presence in the blended MOOC system is a good sign that the teaching presence worked to improve students' performance, engagement and satisfaction. The result fits what was found in earlier studies, which showed that how students saw their teachers affected how they interacted in the classroom and online (Hung & Chou, 2015; Zhang et al., 2016).

Social presence is how connected and socially involved learners feel with others in the learning environment. 91.5% of the survey respondents agreed or strongly agreed that they felt part of a social group in the blended MOOC environment. This high number of responses suggests that the way the course was set up and how technology was used worked well to get students to talk to each other and work together. Therefore, making online learning environments feel like a community and getting people involved is important. This result aligns with what many other studies have found: that is, social presence is a vital part of keeping people interested and satisfied in online and blended learning environments (Garrison & Anderson, 2003; Richardson & Swan, 2003; Wang et al., 2011). The result suggests that there may be ways to improve the social parts of the course, such as by giving students more chances to talk to each other synchronously or by having more structured group activities.

The result on cognitive presence shows that 95.1% of the respondents agreed or strongly agreed that they experienced cognitive presence during online and classroom learning activities. The result is similar to what other studies have found: students agreed with the cognitive constructs of the CoI (Alavi & Taghizadeh, 2013; McKerlich et al., 2011). The positive answers showed that the students were actively building and exploring ideas and making connections between different ideas and what they were learning in class. This activity is an integral part of cognitive presence because it shows that students can use what they learned in meaningful ways in and out of the classroom (Shea & Bidjerano, 2009). The implication is that students could learn new things by interacting with course materials and each other. Knowledge construction is vital to cognitive presence (Akyol & Garrison, 2011; Shea & Bidjerano, 2009) because it shows that students are actively engaged in learning and can take ownership of it. This result suggests that, in general, the course helped students be more cognitively present.

Most participants who answered the questions about learning presence (95.1%) agreed or strongly agreed that they felt they were learning in the blended MOOC system. This finding supports what other studies have found: that students agreed with the CoI's learning presence constructs. (Alavi & Taghizadeh, 2013; McKerlich, et al., 2011). The finding is promising because it shows that the students thought they were learning and improving in the course. Again, there is much learning presence among the study subjects (i.e., high self-regulation and co-regulation in the learning process). This group of respondents said that they thought the blended MOOC method helped them to learn and improve their learning. The result shows that students had a favourable view of learning presence, which aligns with other studies about the topic. For example, research has shown that students are more interested in school and do better when they have more learning presence (Borup et al., 2012; Shea et al., 2010). However, it is also important to note that not all answers were identical. Not everyone agreed with the same things said about learning presence. This difference could be looked into more with subgroup studies or the answers to each question. Based on these results, students felt that they could understand the course topic, keep track of their learning, and connect socially with their peers and the teacher. Many participants who took the course agreed or strongly agreed with these statements, which shows that the course did an excellent job of encouraging learning presence.

This segment of the discussion deals with

Table 6-3 concerning the factors of the Blended MOOC Engagement model.

Table 6-3 displays the aggregations of the Likert responses of the question items from the two constructs of the blended MOOC engagement model (9 and 17 items, respectively, for ME and CBCE). CBCE refers to students' active participation and engagement in courses conducted on campus. The result reveals that a substantial percentage of students (96.2%) express agreement or strong agreement with the CBCE construct. Almutairi (2018) found similar results, using the tool on lecturers. This high level of engagement is consistent with studies on students' engagement in higher education which have shown that engagement is positively related to academic performance, retention, and college satisfaction (Kahu, 2013; Kuh, 2009).

Factors	**Response categories**	**Responses**	
		N	**%**
Campus-base Course Engagement (CBCE)	Strongly disagree	2	0.1
M=4.47, SD= 0.586	Disagree	8	0.3
Mode = 5	Undecided	100	3.5
	Agree	1,304	45.4
	Strongly agree	1,461	50.8
	Total	2,875	100
MOOC Engagement (ME)	Strongly disagree	4	0.1
M=4.41, SD= 0.652	Disagree	28	1.0
Mode = 5	Undecided	155	5.4
	Agree	1,293	45.0
	Strongly agree	1,395	48.5
	Total	2,875	100

Students were intrigued by ME with 93.5% responded positively to its statements. Almutairi (2018) found similar results, using the tool on lecturers. Since student engagement improves learning outcomes and success in online classes, this result is good news (Lin et al., 2021; Kim et al., 2020; Deng et al., 2020). Only a few students had issues with MOOC engagement, suggesting that ME should be improved through strategy such as collaborative and interactive tasks (Lee et al., 2019).

Table 6-3:Likert scale Scores for the factors of the Blended MOOC Engagement model

Source: Fieldwork 2022

The data indicate that students generally have a strong sense of engagement in both CBCE and ME, with a somewhat greater inclination towards CBCE. Nevertheless, it is crucial to acknowledge that the disparities in average scores are generally minor, suggesting that students hold a favourable impression of both forms of engagement.

Factors	**Response categories**	**Responses**	
		N	**%**
Campus-base Course Engagement (CBCE)	Strongly disagree	2	0.1
M=4.47, SD= 0.586	Disagree	8	0.3
Mode = 5	Undecided	100	3.5
	Agree	1,304	45.4
	Strongly agree	1,461	50.8
	Total	2,875	100
MOOC Engagement (ME)	Strongly disagree	4	0.1
M=4.41, SD= 0.652	Disagree	28	1.0
Mode = 5	Undecided	155	5.4
	Agree	1,293	45.0
	Strongly agree	1,395	48.5
	Total	2,875	100

Table 6-4 shows student responses to the blended MOOC acceptance and use question.

Table 6-4:Likert scale Scores for the factors affecting UTAUT for Blended MOOC use

Factors	**Response categories**	**Responses**	
		N	**%**

Performance Expectancy (PE)	Strongly disagree	12	0.4
M=4.37, SD= 0.657	Disagree	19	0.7
Mode = 4	Undecided	155	5.4
	Agree	1,384	48.1
	Strongly agree	1,305	45.4
	Total	**2,875**	**100**
Effort Expectancy (EE)	Strongly disagree	9	0.3
M=4.28, SD= 0.681	Disagree	25	0.9
Mode = 4	Undecided	251	8.7
	Agree	1,468	51.1
	Strongly agree	1,122	39.0
	Total	**2,875**	**100**
Social Influence (SI)	Strongly disagree	7	0.2
M= 4.41, SD= 0.654	Disagree	17	0.6
Mode = 5	Undecided	173	6.0
	Agree	1265	44.0
	Strongly agree	1413	49.1
	Total	**2,875**	**100**
Facilitating Conditions (FC)	Strongly disagree	12	0.4
M= 4.30, SD=0.701	Disagree	35	1.2
Mode = 4	Undecided	230	8.0
	Agree	1,409	49.0
	Strongly agree	1,189	41.4
	Total	**2,875**	**100**
Hedonic Motivation (HM)	Strongly disagree	19	0.7
M= 4.36, SD=0.753	Disagree	32	1.1
Mode = 5	Undecided	275	9.6
	Agree	1,126	39.2

	Strongly agree	1,423	49.5
	Total	**2,875**	**100**
Habit (H)	Strongly disagree	27	0.9
M= 4.32, SD=0.802	Disagree	50	1.7
Mode = 5	Undecided	297	10.3
	Agree	1,090	37.9
	Strongly agree	1,411	49.1
	Total	**2,875**	**100**
Task Value (TV)	Strongly disagree	10	0.3
M= 4.39, SD=0.631	Disagree	14	0.5
Mode = 4	Undecided	128	4.5
	Agree	1,417	49.3
	Strongly agree	1,306	45.4
	Total	**2,875**	**100**
Behavioural Intention (BI)	Strongly disagree	15	0.5
M= 4.34, SD=0.705	Disagree	26	0.9
Mode = 5	Undecided	226	7.9
	Agree	1,317	45.8
	Strongly agree	1,291	44.9
	Total	**2,875**	**100**
Actual Use (AU)	Strongly disagree	26	0.9
M= 4.25, SD=0.844	Disagree	103	3.6
Mode = 4	Undecided	289	10.1
	Agree	1,167	40.6
	Strongly agree	1,290	44.9
	Total	**2,875**	**100**

Source: Fieldwork 2022

Performance expectancy is how much a person feels a particular technology will help them achieve their job goals. Table 6-4 shows that most respondents (93.5%) agreed or strongly agreed. This result suggests that the system supports students in meeting their learning goals. Performance expectations predict technology adoption, as earlier research has shown (Alalwan et al., 2017; Aziz, 2015; Venkatesh et al., 2012; Zuiderwijk et al., 2015). This study suggests that blended MOOC supported learners in meeting their aims.

People's expectations about how well something will work strongly predict their adoption and use. The system's ease of use determines effort expectancy. (Davis, 1989). According to Table 6-4, 90.1% of respondents agreed or strongly agreed that blended MOOCs were easy to use. This result supports earlier studies that showed students would choose EdTech solutions like blended MOOCs if they were easy to use and helped them learn more (Aziz, 2015). The system was easy to use and navigate since most respondents agreed or firmly agreed. The system's user-friendly design, which improves user satisfaction and adoption, explains the high agreement (Venkatesh et al., 2003). The system's ease of use also explains its high approval rating. Effort expectancy can simplify the method and reduce mental effort (Gefen et al., 2003).

Social influence measures how much people believe key people recommend a system or technology. It is how much students think teachers, peers and others think they should use learning technology. In this study, participants rated how much they agreed or disagreed with statements about how others affect them. Table 6-4 shows that most respondents (93.1%) agreed (54.4%) or strongly agreeing (35%) with questions pertaining to social influence. According to past studies, people strongly agreed with the construct (Aziz, 2015), indicating that students believe classmates and teachers wanted them to engage in class.

Facilitating conditions help students learn and finish tasks by providing resources, tools, and support. (Venkatesh et al.,2003). Most respondents to the facilitating conditions construct agreed or strongly agreed that they have the tools and support to use blended MOOCs well. Table 6-4 shows that 41.4% strongly agreed and, 49% agreed with this concept totally 90.4% overall. Previous studies support the statement about facilitating conditions (Aziz, 2015; Maarop & Win, 2011; Zuiderwijk et al., 2015). The result shows that UCC's technological resources and academic support system are adequate and accessible for students to use for learning, which is good. It connotes that students had the facilities to use blended MOOCs and that their experiences would be positive. Suitable learning environments can inspire, engage, and improve student performance. Students believed they had enough resources and support to complete course tasks.

Hedonic motivation is how much someone enjoys using a tool. Table 6-4 shows that 88.7% of respondents thought blended MOOCs were fun. The hedonic motivation was widely accepted, confirming earlier research. (Aziz, 2015; Maarop & Win, 2011; Zuiderwijk et al., 2015). Edutainment and gamification have been recommended for online/blended/MOOC settings because they help students learn while they play (Dicheva et al., 2015; Panyajamorn et al., 2022).

Table 6-4's "Habit" construct shows that most students (87%) agreed or strongly agreed with habit statements. Thus, respondents viewed habits as good influences on blended MOOC use. Some respondents, notably those above level 100, had taken blended MOOCs for two or more semesters and have been using blended MOOCs habitually. It implies that blended MOOC users' actions may be difficult to predict without knowing their usual behaviour.

"Habit" and "hedonic motivation" have similar distributions, suggesting a relationship. Habits and hedonic motivation can predict technology adoption (Bhattacherjee, 2001; Moorthy et al., 2019; Sharif & Raza, 2017; Venkatesh et al., 2012). The low number of "disagree" and "strongly disagree" answers for "Habit" implies that blended MOOCs are easy to use and that the benefits exceed the costs and work. The habit construct is a good predictor of behaviour because it shows how participants have learned to do something naturally. Habit formation is linked to more consistent behaviour and a better ability to maintain a behaviour shift over time. (Gardner et al., 2012; Verplanken & Wood, 2006). Thus, interventions should help participants form habits to alter their behaviour permanently. Thus, encouraging students to use technology more in the classroom may boost blended MOOC appeal.

Task value indicates how much people value a task, activity or work. Table 6-4 for task value shows 94.7 per cent of respondents agreed or strongly agreed with the statements. These results show that most participants think the task will help them to achieve their aims. Despite the overwhelm majority at least agreeing to the statements under this construct, teachers should still explain why the task is essential and why they should do it. Students find course activities valuable and relevant to their learning aims. This claim indicates future students' attitudes towards blended MOOCs. Task value influences course ideas, enrolment, and future web-based learning. (Chiu & Wang, 2008). No matter how strenuous the course or learning activity is, most students will keep working on a helpful task (Eccles et al., 1983).

The behavioural intention can be used to determine if students are ready to use blended MOOCs, which is a crucial factor in figuring out how engaged, satisfied, and performing well at school they are. Most of the students (88.7%) either agreed (52.60%) or strongly agreed (36.1%) that they intend to behave well when using blended MOOCs. Based on the data collected, most students have positive behavioural intentions towards using blended MOOCs. The result fits well with other studies, indicating that blended MOOCs are an excellent way to get a college education (Alraimi et al., 2015; Bonk & Graham, 2012). This good purpose is important for determining how engaged, satisfied, and successful students will be in blended MOOCs. Thus, schools should push and use blended MOOCs to engage students, satisfy them, and help them do better in school. Results show that most students (88.7%) plan to use blended MOOCs in a good way. (i.e., Agree and strongly agree). Based on these results, most students are willing to use blended MOOCs for their learning.

The results of behavioural intention are important for teachers, lawmakers and other researchers to know. As blended MOOCs become more common in higher education, knowing how students feel about them and what they plan to do with them is important. The result of this study shows that most students like blended MOOCs because of the benefits they offer, such as flexibility and ease. Nevertheless, students may only use blended MOOCs if they have a favourable opinion of them. They may consider other things like how easy they are to use, how much effect they have on their peers, and how easy it is for them to learn, which also plays a role. Some of the students might be hesitant or worried about using blended MOOCs based on how different their answers were. Their opinion could be because of things like how hard the course seems, how much help is available, or how good the online tools are.

How likely is it that a user will use the technology in the future to do specific jobs or activities in the real world? Most participants (81.6%) agree or strongly agree that blended MOOCs should be used to learn in the future. This finding fits with what has been found in the past: when the right conditions are in place, participants are willing to use EdTech solutions like blended MOOC (Aziz, 2015). The goal of using technology should be to make people more productive, which in the world of education means helping people learn better. However, others believe that using a system like EdTech should be the end goal (Eyada, 2022). For this reason, this study probes further to determine how satisfied students are and how well they perceive do well academically in using blended MOOCs. The continuous use of EdTech

Factors	**Response categories**	**Responses**	
		N	**Percent**
Students' Satisfaction (SS)	Strongly disagree	11	0.4
M=4.43, SD= 0.626	Disagree	18	0.6
Mode = 5	Undecided	125	4.3
	Agree	1,180	41.0
	Strongly agree	1,541	53.6
	Total	**2,875**	**100**
Perceived Academic Performance (AP)	Strongly disagree	12	0.4
M=4.37, SD= 0.656	Disagree	19	0.7
Mode = 4	Undecided	154	5.4
	Agree	1,389	48.3
	Strongly agree	1,301	45.3
	Total	**2,875**	**100**

solutions determines their satisfaction and usefulness (Joo et al., 2013). Actual use is how much a person thinks technology will help them get where they want to go and do what they want.

The results in this Table indicate that most students "agree" or "strongly agree" with most of the items regarding UTAUT's factors, as shown with their mode of 4 or 5, though their mean scores and standard deviations vary. The UTAUT factor with students' most outstanding positive response is Task Value (TV), with a score of 4.39 and a mode UTAUT factor of 4. About 94.7% of students agreed or strongly agreed. However, Actual Use (AU) received a somewhat less positive reaction, with a mean (M) score of 4.25 and a mode of 4. Students agreed or strongly agreed with 85.5% of items of Actual Use. All UTAUT variables mainly received positive replies, showing that students usually view these aspects positively in the context of blended MOOCs and technology adoption and use.

Table 6-5 shows students' perception of their satisfaction and academic performance in using blended MOOCs.

Table 6-5 shows that 91.3% of the participants who answered said that the blended

Factors	Response categories	Responses	
		N	Percent
Students' Satisfaction (SS)	Strongly disagree	11	0.4
M=4.43, SD= 0.626	Disagree	18	0.6
Mode = 5	Undecided	125	4.3
	Agree	1,180	41.0
	Strongly agree	1,541	53.6
	Total	**2,875**	**100**
Perceived Academic Performance (AP)	Strongly disagree	12	0.4
M=4.37, SD= 0.656	Disagree	19	0.7
Mode = 4	Undecided	154	5.4
	Agree	1,389	48.3
	Strongly agree	1,301	45.3
	Total	**2,875**	**100**

MOOCs learning experience met their needs, either moderately(agree) or intensely(strongly agree). The Student Satisfaction results show that the teachers of the MOOCs and UCC did well in giving most students a good experience. Overall, the fact that the students were thrilled is good for the university. Students' high levels of satisfaction could be caused by several things, such as the quality of teaching, the curriculum's relevance to the student's career goals, the quality of the facilities and the availability of resources and support services (Kandiko & Mawer, 2013; Pekrun et al., 2009). However, suppose universities want to satisfy their students by using blended MOOCs. In that case, they still need to figure out why some students were unsatisfied and fix these problems. It is suggested that the school keep track of what makes students' satisfied and improve on those things (Paraskeva et al., 2008; Pekrun et al., 2009).

Table 6-5:Likert scale Scores for students' satisfaction and perceived academic performance Blended MOOC use

Factors	**Response categories**	**Responses**	
		N	**Percent**
Students' Satisfaction (SS)	Strongly disagree	11	0.4
M=4.43, SD= 0.626	Disagree	18	0.6
Mode = 5	Undecided	125	4.3
	Agree	1,180	41.0
	Strongly agree	1,541	53.6
	Total	**2,875**	**100**
Perceived Academic Performance (AP)	Strongly disagree	12	0.4
M=4.37, SD= 0.656	Disagree	19	0.7
Mode = 4	Undecided	154	5.4
	Agree	1,389	48.3
	Strongly agree	1,301	45.3
	Total	**2,875**	**100**

Source: Fieldwork 2022

Perceived academic performance is important in education; measuring it helps us determine how well educational programmes, teaching methods and learning results work.

Table 6-5's findings on perceived academic performance show that many participants agreed or strongly agreed that the blended MOOC experience helped them do better in school (91.2%). It implies that the manner blended MOOCs were taught and how they were used to learn were thought to help students do better academically. This finding aligns with other studies about blended MOOCs. MOOCs can be just as good for learning and performance as traditional face-to-face courses (Means et al., 2009; Means et al., 2013). However, it is important to remember that not all students are good candidates for online learning and that online learning can have problems like a lack of social contact and technical problems (Parker et al., 2011). Again, the results support studies that have already shown that different types of EdTech interventions can help students do better in school. Most students think they are doing well in school, but they need to be surer or have a better idea of how well they are doing. For example, one study found that children in STEM fields did better in school when they had a mentor (Lin-Siegler et al., 2016). Another study found that a programme that taught college students how to study helped them improve in school. (Dunlosky et al., 2013). However, it is important to remember that how well students think they are doing in school may not always match how well they are

Factors	**Response categories**	**Responses**	
		N	**Percent**
Students' Satisfaction (SS)	Strongly disagree	11	0.4
M=4.43, SD= 0.626	Disagree	18	0.6
Mode = 5	Undecided	125	4.3
	Agree	1,180	41.0
	Strongly agree	1,541	53.6
	Total	**2,875**	**100**
Perceived Academic Performance (AP)	Strongly disagree	12	0.4
M=4.37, SD= 0.656	Disagree	19	0.7
Mode = 4	Undecided	154	5.4
	Agree	1,389	48.3
	Strongly agree	1,301	45.3
	Total	**2,875**	**100**

doing. (Kuncel et al., 2013). In future studies, grades or test scores could be used as objective measures of academic success to understand better how the intervention affected students. The data show that most students think they are doing well in using blended MOOCs at UCC. When figuring out what the result denotes, it is vital to consider the study's flaws, like the fact that the data was self-reported and that the sample may need to be more representative of the whole school population. Also, it is essential to think about what parts of the online learning environment may have influenced how students thought it changed their grades. For example, the quality of the teaching, the availability of tools and support, and the flexibility of the online format all played a part.

Student satisfaction with blended MOOCs was high. A large majority of students supported this conclusion. About 94.6% of students liked blended MOOCs. This result supports prior studies showing that blended MOOCs improve student satisfaction (Albó et al., 2015; Rambe & Moeti, 2017). Blended MOOCs offer flexible learning, high-quality resources, and interactive learning, which satisfy students.

Blended MOOCs improved students' academic performance but less than satisfaction. About 93.6% of students said blended MOOCs improved their academic performance. This result also shows that students think blended MOOCs improve academic success. Integrating MOOC resources, interactive content, and additional materials can increase learning results (Watson et al., 2016; Giasiranis & Sofos, 2020). Students report excellent satisfaction and positive academic success when using blended MOOCs. These data also suggest blended MOOCs in higher education may improve learning and academic outcomes.

6.5 Test for Multivariate normality

Multivariate normality testing is necessary for many statistical methods. Kline (2015) recommended the following tests to determine multivariate normality:

- Multivariate Kurtosis and Skew Tests: These tests use data skewness and kurtosis to test multivariate normality.
- Mardia's Test: This test tests multivariate normalcy using data skewness and kurtosis.

Skewness and kurtosis were evaluated for univariate and multivariate data distribution or models. Table 6-6 shows the skewness and kurtosis values of each construct under study.

Table 6-6:Skewness and Kurtosis values for the constructs

Constructs	Skewness	SE_skew	Z_skew	Kurtosis	SE_kurt	Z_kurt
Perceived Academic Performance (AP)	-1.027	0.046	-22.488	3.413	0.091	37.384
Actual use (AU)	-1.122	0.046	-24.573	2.072	0.091	22.695
Behavioural intention (BI)	-1.143	0.046	-25.022	3.363	0.091	36.844
Cognitive presence (CP)	-1.109	0.046	24.278	3.357	0.091	36.774
Effort Expectancy (EE)	-0.867	0.046	-18.997	2.735	0.091	29.966
Facilitating conditions (FC)	-0.923	0.046	-20.206	2.288	0.091	25.063
Habit (H)	-1.183	0.046	-25.916	2.405	0.091	26.347
Hedonic Motivation (HM)	-1.118	0.046	-24.487	2.477	0.091	27.137
Learning presence (LP)	-1.128	0.046	-24.704	3.552	0.091	38.913
Performance Expectancy (PE)	-1.108	0.046	-24.259	4.041	0.091	44.262
Student Engagement (SE)	-0.771	0.046	-16.883	2.495	0.091	27.336
Social influence (SI)	-0.893	0.046	-19.550	2.969	0.091	32.519
Social presence (SP)	-1.095	0.046	-23.987	2.810	0.091	30.782

Student Satisfaction (SS)	-1.121	0.046	-24.550	4.492	0.091	49.204
Task value (TV)	-0.977	0.046	-21.392	3.765	0.091	41.242
Teaching presence (TP)	-1.097	0.046	-24.027	3.615	0.091	39.595

A look at Table 6-6 shows that the skewness values range from -1.183 to -0.771, all of which are within ± 2. Again, the kurtosis values range from 2.072 to 4.492, all of which are within ± 7. Thus, all constructs in this research have absolute values of skewness and kurtosis that are less than or equal to 2 and 7, respectively. Therefore, per Kline's (2015) suggestion that a skewness or kurtosis with an absolute value of more than 3 or 10, respectively, all the variables examined in this study exhibit skewness and kurtosis values that fall within the acceptable range of ±3 for skewness and ±10 for kurtosis.

As part of this study, Mardia's test was used to look at the multivariate skewness and kurtosis. Table 6-7 presents the values for skewness and kurtosis for all constructs, using Mardia's multivariate skewness and kurtosis.

Table 6-7:Skewness and Kurtosis values for all constructs

	b	**z**	**p-value**
Skewness	54.4311	26081.5711	0
Kurtosis	643.0916	396.6597	0

The values for Mardia's coefficient for multivariate skewness with b=54.4311 for the coefficient show that the data are skewed significantly. The very big z-value indicates that this deviation from normality is statistically significant. Again, Mardia's coefficient for multivariate kurtosis b=643.0916 and z=396.6597 imply that the kurtosis of the multivariate data distribution is significantly different from normality. This result shows that the data have a heavy peaked distribution. These results show that the data are not distributed in a normal way and may have heavier tails and a more pronounced peak on the right than a normal distribution (West et al., 1995). Moreover, the null hypothesis for Mardia's multivariate skewness and kurtosis coefficients are that the sample has a multivariate normal distribution i.e., the sample data are neither skewed nor kurtotic. However, the p-values for both are zero indicating that the null hypothesis is rejected. Thus, the sample data have multivariate skewness and kurtosis indicating that the data does not follow a multivariate normal distribution.

The results indicate that the data distribution could be more extensive, posing a challenge when employing SEM analysis, which presupposes a normal distribution of data dispersion. Using SEM on data that does not follow a normal distribution can generate bias in estimating parameters and standard errors, leading to inaccurate conclusions. Several alternative strategies can be employed to mitigate the non-normalcy issue and enhance the data's adherence to the assumption of normality. Two approaches can be used to enhance the analysis. Firstly, non-linear transformations, such as the natural logarithm and square root, can be applied to the variables of interest. Secondly, alternative estimation methods, such as Weighted Least Squares (WLS), Diagonally Weighted Least Squares (DWLS), or Robust Maximum Likelihood (MLR), can be utilised instead of the traditional Maximum Likelihood Estimation (MLE). These alternative methods are less affected by non-normality and can provide more robust results (CenterStat, 2019; PsychometStats, 2022). The estimations above are commonly employed in software systems, including Lisrel, AMOS, Mplus, and R, to address non-normal data distributions within the framework of structural equation modelling (SEM). According to Kline (2011), certain distributions may exhibit such extreme non-normality that transformation methods are ineffective (p. 64).

One potential approach for addressing non-normal distributions is the utilisation of the bootstrapping technique (Nevitt & Hancock, 2001), which is available in many structural equation modelling (SEM) software programs such as SmartPLS, AMOS, Mplus, and R (specifically, the lavaan package). Bootstrapping is a statistical technique that resamples a given dataset with replacement to generate many simulated samples. The bootstrap method estimates parameters, standard errors, and p-values for model test statistics using empirical sampling distributions from a substantial number of generated samples (Nevitt & Hancock, 2001). The bootstrapping technique is applicable for estimating a wide range of statistics, provided that researchers can compute them using their sample data. These statistics include but are not limited to, the mean, median, mode, variance, standard deviation, skewness, kurtosis, correlation coefficient, regression coefficients, and confidence intervals (Nevitt & Hancock, 2001; Varian, 2005). According to Lai (2018), the Bootstrap method demonstrates resilience in the face of model misfit and non-normality, mainly when these issues are of moderate to severe concern or when the sample size is not excessively big. Factor Analysis (EFA, CFA) and Structural Equation Modelling (SEM) are statistical techniques commonly employed in research studies. These approaches are particularly suitable for large sample sizes since the size of the sample directly impacts the accuracy and consistency of the results.

Chernick (2011) posits that the bootstrap method is effective for large samples, as smaller sample sizes often yield bootstrapped results that need to be sufficiently accurate (Yung & Bentler, 1996). Consequently, when utilising bootstrapped samples, it is necessary to have access to a substantial existing dataset to ensure the reliability of the findings (Brown, 2015; Kyriazos, 2018). The present study possesses a considerable sample size of 2,875, surpassing the recommended sample size of over 200, as Nevitt and Hancock (2001) suggested for bootstrap analysis. This larger sample size is advantageous in generating less biased estimates for a measurement model, particularly when compared to estimates obtained through standard maximum likelihood (ML) estimation in situations characterised by non-normality. Thus, is improbable that these factors will significantly affect the integrity of the subsequent analysis using the SEM method. However, before doing the structural equation modelling (SEM) analysis, it is imperative to evaluate the sufficiency of the sample by employing the Kaiser-Meyer-Olkin (KMO) measure and scrutinising the sphericity of the distribution via Bartlett's test.

6.6 KMO and Bartlett's test of sphericity

Table 6-8 displays the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy and Bartlett's test of sphericity. The Kaiser-Meyer-Olkin (KMO) measure and Bartlett's Test of Sphericity (BTS) are two commonly employed statistical tests within the context of exploratory factor analysis (EFA) to assess the appropriateness of utilising factor analysis as a methodological approach for analysing a given dataset. The KMO measure ranges from 0 to 1, and it is widely acknowledged that values of 0.6 or above are deemed satisfactory. A low Kaiser-Meyer-Olkin (KMO) statistic suggests that the dataset is inappropriate for factor analysis. Simultaneously, a high Kaiser-Meyer-Olkin (KMO) value indicates that the collected data will likely yield precise and dependable outcomes.

The BTS test evaluates whether or not the correlation matrix of variables can be used effectively in factor analysis. The purpose of this test is to determine whether or not there is a statistically significant association between the variables by determining whether or not the correlation matrix is equal to the identity matrix. Factor analysis can be helpful if there is a large gap between the two variables. If the p-value is less than 0.05, then the null hypothesis should be rejected and factor analysis should be used.

Table 6-8:KMO and Bartlett's test values of the constructs

		Bartlett's Test		
Constructs	**KMO**	**Approx. Chi-Square**	**df**	**Sig.**
TP	0.964	20592.759	78	0
SP	0.967	21887.272	78	0
SP	0.967	21887.272	78	0
CP	0.964	19705.38	66	0
LP	0.977	40688.586	276	0
CBCE	0.957	22552.615	136	0
ME	0.916	12075.8	36	0
PE	0.872	6402.782	10	0
EE	0.83	4573.044	10	0
SI	0.931	10986.318	28	0
FC	0.883	7013.417	15	0
HM	0.74	4296.241	3	0
H	0.725	3881.516	3	0
TV	0.906	8305.376	15	0
SS	0.896	7158.98	15	0
AP	0.872	6650.1	10	0
AU	0.813	4906.322	6	0

An initial examination of the 16 constructs was performed to assess their suitability for structural equation modelling. The consensus among individuals is that a KMO value equal to or exceeding 0.5 is considered favourable (Thao, Van Tan & Tuyet, 2022). The Kaiser-Meyer-Olkin (KMO) values for all 16 constructs fell within 0.725 to 0.977, satisfying the stipulated criterion. To determine whether or not the correlation matrix is indeed identity-matrix-like, the researcher used Bartlett's test of sphericity. This statement implies no interdependencies among the factors assuming a significance level of less than 0.05(Thao, et al., 2022). In this scenario, the interrelationships among the variables exhibit significant strength, thereby indicating the potential utility of employing factor analysis. Bartlett's test produced a statistically significant outcome ($p < 0.05$) for all 16 constructs, indicating that the intercorrelations among the factors were sufficiently strong to warrant conducting a factor analysis. The suitability of the 16 constructs for structural equation modelling has been determined based on the KMO measure and Bartlett's test results.

6.7 Summary

This chapter analysed the descriptive data of the study. The data was analysed using descriptive statistics, including frequencies, percentages, means, medians, and modes. The data were grouped according to different aspects of the study, such as the bio-demographic data of the respondents (Table 6-1), revised CoI (Table 6-2), blended MOOC engagement (

Table 6-3)extended UTAUT (Table 6-4) and endogenous constructs of students' satisfaction and perceived academic performance (

Table 6-5). Most participants, comprising more than 75% of the total respondents,

Factors	Response categories	Responses	
		N	Percent
Students' Satisfaction (SS)	Strongly disagree	11	0.4
M=4.43, SD= 0.626	Disagree	18	0.6
Mode = 5	Undecided	125	4.3
	Agree	1,180	41.0
	Strongly agree	1,541	53.6
	Total	**2,875**	**100**
Perceived Academic Performance (AP)	Strongly disagree	12	0.4
M=4.37, SD= 0.656	Disagree	19	0.7
Mode = 4	Undecided	154	5.4
	Agree	1,389	48.3
	Strongly agree	1,301	45.3
	Total	**2,875**	**100**

Factors	Response categories	Responses	
		N	%
Campus-base Course Engagement (CBCE)	Strongly disagree	2	0.1
M=4.47, SD= 0.586	Disagree	8	0.3
Mode = 5	Undecided	100	3.5
	Agree	1,304	45.4
	Strongly agree	1,461	50.8
	Total	2,875	100
MOOC Engagement (ME)	Strongly disagree	4	0.1
M=4.41, SD= 0.652	Disagree	28	1.0
Mode = 5	Undecided	155	5.4
	Agree	1,293	45.0
	Strongly agree	1,395	48.5
	Total	2,875	100

expressed agreement or strong agreement when rating a statement on a 5-point Likert scale. The statistical measures of central tendency, namely the mean, mode, and median, converged at 4. Parametric and non-parametric statistical methods are employed to assess the normality of a distribution. Parametric tests are predicated upon adherence to statistical assumptions, such as data distribution. Non-parametric tests are not reliant on the assumption of specific probability distributions. Therefore, the statistical measures of skewness and kurtosis were assessed for each construct (univariate analysis) and collectively (multivariate analysis). All constructs examined in this investigation adhered to the established criteria for univariate normality, with skewness values falling within the range of ±3 and kurtosis values within the range of ±10. The multivariate skewness and kurtosis coefficients calculated by Mardia indicated the absence of skewness or kurtosis concerning multivariate normality. The absence of skewness and kurtosis in the distribution was not supported by p-values of zero. This observation suggests the presence of multivariate skewness and kurtosis. Nevertheless, it is worth noting that the sample size of 2,875 was sufficiently large, and the skewness value fell within the range of -1 to +1. Consequently, it is improbable that this would significantly impact the standard error of the mean (SEM) or other statistical analyses conducted. The adequacy of the sample for structural equation modelling (SEM) analysis was evaluated using the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's Sphericity (BTS) test, as presented in Table 6-6. All sixteen structures in the study satisfied the Kaiser-Meyer-Olkin (KMO) criteria, with values ranging from 0.725 to 0.977. Bartlett's test yielded a high significance level ($p < 0.05$) across all 16 constructs, suggesting robust correlations among the components for factor analysis. The measuring scale will be thoroughly analysed in Chapter 8 to ensure instrument validity and reliability.

CHAPTER 7: MEASUREMENT SCALE ANALYSIS

7.1 Introduction

This chapter discussed the measurement model from the Partial Least Squares Structural Equation Modelling (PLS-SEM) in SmartPLS version 4.0.8.1. Measurement scale analysis is crucial to research because it verifies the constructs for which data has been gathered. This chapter examines measurement scale analysis to assess the study's constructs' robustness. The chapter examines internal consistency reliability, concept validity, discriminant validity, multicollinearity, and model fit, which are critical to measuring scale quality. First, Section 8.2 examines internal consistency reliability, which measures how consistently items on the same construct connect. This section uses Cronbach's alpha, composite reliability, and reliability coefficient to assess construct reliability and consistency. Further, Section 8.3 emphasises construct validity, which is essential to measurement scale analysis. Convergent validity examines how well several measures of the same construct converge. Convergent validity components like outer loadings and average variance are examined. Section 8.4 explains discriminant validity and its importance in distinguishing constructs. Cross-loadings, Fornell and Larcker criteria, and the Heterotrait-Monotrait (HTMT) correlation ratio are utilised to assess the discriminant validity of this study's constructs. An examination of how multicollinearity affects the constructs' stability and robustness is discussed in Section 8.5. The final component, 8.6, evaluates model fit. To accurately represent the phenomena, constructs need a good model. Model fit is assessed using several criteria to validate the measurement scale.

The data acquired from the study were subsequently analysed using the Partial Least Squares Structural Equation Modelling (PLS-SEM) technique in SmartPLS version 4.0.8.1. A path model is a graphical representation that illustrates the hypotheses and relationships between variables in a structural equation modelling (SEM) analysis, as Bollen (2002, as cited in Sarstedt et al., 2021) described. A path model includes structural and measurement models. In PLS-SEM, the outer models are measurement models, while the inner models are structural. The measurement model deals with the individual questionnaire items and respective latent variables (constructs) measured by the former (Sarstedt et al., 2021). The structural model shows the cause-and-effect relationships that deal with the latent variables and their linking relationships (Sarstedt et al., 2021).

Two stages are involved in the analysis of PLS-SEM. The first is to analyse the validity and reliability of the measurement model. After successfully passing the validity and reliability tests, the subsequent step involves the analysis of the structural model, as Hair et al. (2014) outlined. In light of this, Yeboah and Nyagorme (2020), citing Hair et al. (2014), suggested that the following elements be evaluated in order to evaluate the study's measuring model:

- The internal consistency was assessed by looking at both the composite reliability and the reliability of individual indicators.
- Convergent validity can be evaluated by computing the average variance extracted.
- Using the Heterotrait-Monotrait Ratio (HTMT) and the Fornell-Larcker criterion can evaluate discriminant validity.
- Cross-loading of items.

7.2 Internal consistency reliability

Internal consistency is usually judged by how items on the same construct relate to each other (Sarstedt et al., 2021). It checks whether there is a link between the scores on different items meant to measure the same construct. Thus, a way to tell if a construct is valid is to look at its consistency with items. It is also called internal reliability or internal consistency reliability. Each construct's reliability or consistency was examined using statistical methods such as Cronbach's alpha, rho_A, composite reliability, and average variance extracted.

Table 7-1:Outer Loadings, Construct Validity and Reliability of factors for the Measurement Model

Construct	Items	Outer Loadings	Cronbach's alpha	Reliability coefficient rho_A	Composite Reliability rho_C	Average Variance Extracted (AVE)
Academic Performance (AP)	AP1	0.815	0.843	0.844	0.895	0.680
	AP2	0.833				
	AP3	0.834				
	AP4	0.816				
Actual Use (AU)	AU1	0.820	0.854	0.855	0.901	0.695
	AU2	0.820				
	AU3	0.858				
	AU4	0.836				
Behavioural Intention (BI)	BI1	0.769	0.868	0.868	0.904	0.654
	BI2	0.796				
	BI3	0.831				
	BI4	0.829				
	BI5	0.818				
Cognitive Presence (CP)	CPE1	0.771	0.920	0.920	0.933	0.609
	CPE2	0.788				
	CPE3	0.779				

Construct	Items	Outer Loadings	Cronbach's alpha	Reliability coefficient rho_A	Composite Reliability rho_C	Average Variance Extracted (AVE)
	CPI1	0.781				
	CPI2	0.793				
	CPI3	0.798				
	CPR1	0.771				
	CPR2	0.774				
	CPTE3	0.766				
Effort Expectancy (EE)	EE1	0.741	0.814	0.823	0.871	0.576
	EE2	0.792				
	EE3	0.733				
	EE4	0.814				
	EE5	0.800				
Facilitating Conditions (FC)	FC1	0.776	0.864	0.865	0.898	0.595
	FC2	0.771				
	FC3	0.717				
	FC4	0.792				
	FC5	0.768				
	FC6	0.802				

Construct	Items	Outer Loadings	Cronbach's alpha	Reliability coefficient rho_A	Composite Reliability rho_C	Average Variance Extracted (AVE)
Habit (H)	H1	0.882	0.854	0.855	0.912	0.775
	H2	0.898				
	H3	0.860				
Hedonic Motivation (HM)	HM1	0.888	0.871	0.872	0.921	0.795
	HM2	0.902				
	HM3	0.886				
Learning Presence (LP)	LPER1	0.740	0.943	0.943	0.950	0.558
	LPER2	0.727				
	LPER3	0.733				
	LPMSR1	0.756				
	LPMSR2	0.757				
	LPMSR3	0.748				
	LPMSR4	0.753				
	LPMSR5	0.759				
	LPMSR6	0.770				
	LPMSR7	0.769				
	LPMSR8	0.753				

Construct	Items	Outer Loadings	Cronbach's alpha	Reliability coefficient rho_A	Composite Reliability rho_C	Average Variance Extracted (AVE)
	LPMSR9	0.759				
	LPSEL2	0.707				
	LPSEL3	0.728				
	LPSEL4	0.739				
Performance Expectancy (PE)	PE1	0.810	0.844	0.844	0.895	0.682
	PE2	0.833				
	PE3	0.838				
	PE4	0.821				
Student Engagement (SE)	CBCE3	0.720	0.861	0.862	0.894	0.546
	CBCE4	0.733				
	CBCE5	0.738				
	CBCE6	0.735				
	ME2	0.752				
	ME3	0.747				
	ME4	0.747				
Social Influence (SI)	SI1	0.732	0.899	0.899	0.919	0.586
	SI2	0.760				

Construct	Items	Outer Loadings	Cronbach's alpha	Reliability coefficient rho_A	Composite Reliability rho_C	Average Variance Extracted (AVE)
	SI3	0.778				
	SI4	0.791				
	SI5	0.772				
	SI6	0.778				
	SI7	0.749				
	SI8	0.760				
Social Presence	SPAE1	0.709	0.938	0.938	0.946	0.573
	SPAE2	0.734				
	SPAE3	0.739				
	SPAE4	0.764				
	SPAE5	0.770				
	SPGC1	0.712				
	SPGC2	0.758				
	SPGC3	0.764				
	SPGC4	0.764				
	SPOC1	0.774				
	SPOC2	0.785				

Construct	Items	Outer Loadings	Cronbach's alpha	Reliability coefficient rho_A	Composite Reliability rho_C	Average Variance Extracted (AVE)
	SPOC3	0.795				
	SPOC4	0.766				
Student Satisfaction (SS)	SS1	0.736	0.869	0.869	0.902	0.604
	SS2	0.787				
	SS3	0.795				
	SS4	0.796				
	SS5	0.777				
	SS6	0.772				
Teaching Presence (TP)	TPDI1	0.758	0.933	0.934	0.942	0.555
	TPDI2	0.751				
	TPDI3	0.742				
	TPDO1	0.701				
	TPDO2	0.725				
	TPDO3	0.730				
	TPDO4	0.721				
	TPF1	0.739				
	TPF2	0.769				

Construct	Items	Outer Loadings	Cronbach's alpha	Reliability coefficient rho_A	Composite Reliability rho_C	Average Variance Extracted (AVE)
	TPF3	0.766				
	TPF4	0.772				
	TPF5	0.752				
	TPF6	0.754				
TV	TV1	0.755	0.887	0.887	0.914	0.639
	TV2	0.786				
	TV3	0.820				
	TV4	0.807				
	TV5	0.817				
	TV6	0.808				

7.2.1 Cronbach's alpha

Cronbach's alpha (α) is a simple way to determine a score's reliability. It is used when more than one item measures the same underlying concept (Sarstedt et al., 2021). The alpha value depends on how many indicator items are, how similar they are, and how many dimensions they have. The Cronbach's alpha coefficients are typically expected to range between 0 and 1. However, it is worth noting that in some instances, negative values may also be obtained. A negative value indicates the presence of data anomalies, precisely data entry errors. For example, the researcher forgot to give some items a negative score. A small number of questions, objects that do not fit well, or diverse sorts of structures can lower alpha (Tavakol & Dennick, 2011). A Cronbach's alpha coefficient of 0.70 or greater is considered favourable, while a coefficient of 0.80 or greater is deemed more desirable. The range of 0.90 to 0.95 is considered optimal, with values exceeding 0.95 indicative of potential issues. However, Vaske and colleagues opined that the alphas between 0.65 and 0.80 (*i.e.*, $0.65 \leq \alpha \leq 0.80$) are fine (Vaske et al., 2017; Yaghoubi Farani et al., 2019). Cronbach's alpha exhibits certain limitations, as noted by Tavakol and Dennick (2011). Specifically, it has been observed that scores characterised by a higher number of low items tend to exhibit reduced reliability. Additionally, the size of the sample can influence the outcomes of Cronbach's alpha. Alphas in fourth columns of Table 7-1 were above 0.701, passing the minimum threshold and making the items appropriate for each construct in the model.

7.2.2 Composite reliability

Jöreskog's (1995) composite reliability is a statistical measure used to assess the internal consistency of scale items. It serves a similar purpose as Cronbach's alpha, as Netemeyer et al. (2003) discussed. It assesses the reliability of a set of items when loaded on a latent construct. Composite reliability thresholds are still a matter of contention, with varying recommendations from researchers. A reasonable threshold can be anywhere from 0.60 and up (Nunnally & Bernstein, 1994; Shivdas et al., 2020). The complexity of a construct is very variable with respect to its number of components. Fewer items on a scale mean poorer reliability, with more items producing improved reliability. Netemeyer and his colleagues claim it is "realistic" for a five- to eight-item construct to yield 0.80 (Netemeyer et al., 2003). Within the realm of exploratory research, it is generally accepted that composite reliability ratings within the range of 0.60 to 0.70 are deemed acceptable; furthermore, ratings falling between 0.70 and 0.90 are considered indicative of an adequate to good level of reliability. Composite reliability scores above 0.90 (and especially above 0.95) show that some indicators are the same, hurting construct validity (Diamantopoulos et al., 2012).

The composite reliability estimates for the constructs are presented in the sixth column of Table 7-1.The composite reliability estimates varied between 0.871 (EE) and 0.950 (LP). The estimated values for the composite reliability of each construct exceeded the recommended minimum threshold of 0.70(Hair et al., 2014; Hair et al., 2010; Fornell & Larcker, 1981).

7.2.3 Reliability coefficient

Cronbach's alpha underestimates how reliable both latent variable scores are, while composite reliability overestimates their reliability (Dijkstra & Henseler, 2015). Dijkstra and Henseler (2015) developed the reliability coefficient with precision and consistency. According to Hair et al. (2021), it was observed that Cronbach's alpha tends to yield conservative reliability estimates, while composite reliability tends to yield more liberal estimates. However, the actual reliability of a construct typically falls within the range between these two extremes. Hence, the reliability coefficient generally falls within the spectrum encompassing Cronbach's alpha and the composite reliability.

The rho_A value can be between 0 and 1; the more reliable an item scale is, the higher the rho_A value. Higher rho_A values show more reliable item scales. The rho_A value of 0.7 is the bottom limit of adequacy (Ahmad & Hussain, 2019; Prasetyo et al., 2022). The results of the reliability coefficients of each construct are shown in the fifth column of Table 7-1. By inspection, rho_A values range from 0.823 (EE) to 0.943 (LP). All the constructs met the recommended threshold, indicating that the values for reliability were significant and acceptable.

7.3 Construct validity

Construct validity is how well each item indicator assesses its intended idea or construct (Sarstedt et al., 2021). Assessing construct validity is especially important when researching latent constructs, which cannot be directly measured or observed; thus, measurable indicators are needed. Convergent and discriminant validity are used to examine construct validity, and when both prerequisites are met, a test has construct validity (Sarstedt et al., 2021). Convergent validity measures how similar indicators relating to the same construct are identical (Sarstedt et al., 2021). In such a case, the indicators should have a strong correlation. Discriminant validity tests whether theoretically unrelated constructs have unrelated indicators. In such a case, the indicators should have no or weak correlation (Sarstedt et al., 2021).

7.3.1 Convergent Validity

Convergent validity refers to the extent to which the indicators of a particular concept exhibit consistent alignment in their measurements. The process involves elucidating the differences among the various items. Examining the outer loadings of the various items and calculating the average variance extracted (AVE) allowed us to check the convergent validity of the constructs.

7.3.1.1 Outer loadings

From Sarstedt et al. (2021), when the outer loadings of the indicator items that measure a construct are high, the items that make up that construct have a lot to share in common (higher commonalities). This situation is termed indicator reliability. According to the recommendation by Hair et al. (2017), loadings of 0.708 or above are considered statistically significant. When the indicator's loading is above 0.708, it denotes that the construct accounts for more than 50% of the indicator's variance, signalling that the indicator has sufficient item reliability (Sarstedt et al., 2021). Though enormous studies have suggested that outer loadings of 0.50 indicate low but significant reliability (Afthanorhan, 2013; Hair et al., 2019; Hair et al., 2012; Hulland, 1999), the researcher eliminated all items that showed outer loadings lower than 0.70 during the initial analysis because they were less significant, as per Hair et al. (2017). The removed items were coded as CEBE 1, CEBE 2, CEBE 7, CEBE 8, CEBE 9, CEBE 10, CEBE 11, CEBE 12, CEBE 13, CEBE 14, CEBE 15, CPTE1, CPTE2, CPR3, LPER4, LPMSR10, LPSEL1, ME1, ME5, ME6, ME7 and PE5. Thus, the remaining items showed item loadings ranging from 0.711(TV5) to 0.95 (CPE1), as presented in the third column of Table 7-1. These values indicate that the remaining items had significant indicator reliability and were included in the main study.

7.3.1.2 Average variance extracted

From Sarstedt et al. (2021), the average variance extracted (AVE) shows the variance of each indicator item that is explained by its construct. AVE compares a construct's variance to measurement error. AVE assesses the extent to which the variance observed in a construct can be attributed to the construct rather than measurement error (Fornell & Larker, 1981; Hair et al., 2017). To calculate AVE, square each indicator's loading and calculate the average. AVE for each construct is calculated by summing the squares of the standard errors of the indicator variances and then, dividing by that amount. An acceptable value for AVE is 0.50 (Fornell & Larker, 1981). The seventh column of Table 7-1 shows that the measurement model's AVE values range from 0.546 to 0.795. The observation is that they were all more than the minimal value, making them acceptable. The indicator's outer loadings and AVE both pointed that the remaining components of the measurement model possessed substantial convergent validity.

7.3.2 Discriminant Validity

Discriminant validity pertains to the degree to which a latent variable exhibits dissimilarity from other latent variables. and, thus, represents a phenomenon that other latent variables do not represent (Yeboah, 2020). Discriminant validity, sometimes called "divergent validity," looks at whether or not two things that are not supposed to be related are not. The discriminant validity method determines how unique the constructs being looked at are. The discriminant validity assumes that there will be little correlation between two tests that measure different things (Nikolopoulou, 2022). If they do, there is no way to know they are not measuring the same thing. Thus, their discriminant validity shows how much the two ideas are different. Since the two measurements are different, there should be little or no correlation between them. One way to judge the discriminant validity of a test is to show that there is little or no correlation between measures of constructs (Nikolopoulou, 2022). The correlation between two ideas that do not go together will likely be weaker than the correlation between two things that go together (Nikolopoulou, 2022).

In Smart PLS, there are three ways to determine if a discriminant is valid. These are using a) Fornell and Larcker's criteria, b) Cross loadings and c) the Heterotrait-Monotrait (HTMT) ratio of correlation.

7.3.2.1 Cross-loadings

Cross-loadings are when an item significantly affects not just one but other factors (Sarstedt et al., 2021). Items that load on two (or more) factors or a different factor than intended are said to have cross-loadings (Hair et al., 2017). The cross-loading principle posits that an item's loadings on its parent construct should exhibit greater magnitude than on any other research construct. Assume that an item exhibits higher loading on a distinct construct than its parent construct. It means the construct is not discriminatory and must be validated and improved to meet the standard. According to Yeboah (2020) and Yeboah and Nyagorme (2020), measurement items have significant convergent validity when their cross-loadings are estimated to be at least 0.708 and are higher on their respective constructs than their loadings on other constructs. As shown in Table 7-2, the items used in the study that remained after removing those with lower outer loadings had the highest cross-loadings on their respective constructs (bolded) than other constructs. They were all greater than the minimum recommended value. Thus, the instrument was found to have significant discriminant validity and was suitable for the study.

Table 7-2:Discriminant Validity using Indicator Items' Cross Loadings

	AP	AU	BI	CP	EE	FC	H	HM	LP	PE	SE	SI	SP	SS	TP	TV
AP1	**0.815**	0.345	0.493	0.399	0.451	0.407	0.363	0.373	0.433	0.454	0.465	0.47	0.36	0.562	0.368	0.518
AP2	**0.833**	0.36	0.494	0.389	0.454	0.445	0.379	0.399	0.452	0.448	0.495	0.488	0.365	0.551	0.381	0.517
AP3	**0.834**	0.328	0.477	0.393	0.433	0.388	0.343	0.357	0.445	0.439	0.481	0.472	0.338	0.567	0.363	0.536
AP4	**0.816**	0.431	0.514	0.422	0.479	0.469	0.428	0.434	0.461	0.483	0.499	0.506	0.358	0.579	0.382	0.521
AU1	0.31	**0.82**	0.511	0.342	0.45	0.481	0.46	0.4	0.351	0.415	0.403	0.44	0.34	0.398	0.261	0.329
AU2	0.328	**0.82**	0.481	0.346	0.448	0.501	0.453	0.406	0.367	0.379	0.403	0.432	0.373	0.394	0.281	0.328
AU3	0.418	**0.858**	0.562	0.378	0.497	0.492	0.476	0.444	0.424	0.458	0.459	0.498	0.378	0.467	0.315	0.43
AU4	0.419	**0.836**	0.543	0.39	0.473	0.499	0.444	0.45	0.398	0.446	0.458	0.485	0.387	0.447	0.318	0.412
BI1	0.418	0.52	**0.769**	0.39	0.475	0.47	0.464	0.447	0.382	0.506	0.433	0.48	0.371	0.477	0.334	0.418
BI2	0.503	0.464	**0.796**	0.45	0.504	0.444	0.439	0.457	0.441	0.523	0.492	0.517	0.406	0.542	0.382	0.505
BI3	0.508	0.52	**0.831**	0.405	0.519	0.483	0.491	0.472	0.436	0.506	0.468	0.522	0.404	0.542	0.345	0.47
BI4	0.503	0.513	**0.829**	0.449	0.501	0.462	0.48	0.479	0.454	0.505	0.486	0.525	0.395	0.544	0.383	0.498
BI5	0.494	0.529	**0.818**	0.437	0.511	0.479	0.496	0.475	0.466	0.508	0.497	0.539	0.412	0.55	0.359	0.503
CBCE3	0.433	0.354	0.408	0.469	0.462	0.446	0.39	0.391	0.523	0.461	**0.72**	0.508	0.437	0.469	0.413	0.46
CBCE4	0.437	0.387	0.43	0.461	0.457	0.445	0.389	0.4	0.503	0.481	**0.733**	0.486	0.411	0.45	0.382	0.441
CBCE5	0.434	0.373	0.411	0.465	0.464	0.448	0.388	0.379	0.504	0.468	**0.738**	0.482	0.417	0.458	0.37	0.475
CBCE6	0.426	0.347	0.405	0.458	0.476	0.431	0.384	0.397	0.513	0.457	**0.735**	0.487	0.4	0.45	0.39	0.476
CPE1	0.361	0.355	0.395	**0.771**	0.411	0.412	0.382	0.386	0.509	0.421	0.497	0.422	0.498	0.414	0.451	0.418

	AP	AU	BI	CP	EE	FC	H	HM	LP	PE	SE	SI	SP	SS	TP	TV
CPE2	0.384	0.34	0.433	**0.788**	0.445	0.445	0.403	0.43	0.544	0.444	0.511	0.449	0.537	0.451	0.485	0.433
CPE3	0.361	0.361	0.403	**0.779**	0.418	0.435	0.398	0.413	0.495	0.434	0.473	0.438	0.526	0.413	0.478	0.409
CPI1	0.395	0.332	0.428	**0.781**	0.435	0.414	0.395	0.391	0.502	0.434	0.482	0.453	0.532	0.445	0.486	0.433
CPI2	0.374	0.325	0.407	**0.793**	0.425	0.412	0.382	0.392	0.527	0.426	0.494	0.445	0.526	0.438	0.477	0.426
CPI3	0.4	0.343	0.41	**0.798**	0.412	0.405	0.378	0.397	0.525	0.429	0.503	0.441	0.532	0.419	0.48	0.437
CPR1	0.392	0.332	0.407	**0.771**	0.418	0.412	0.38	0.399	0.51	0.429	0.492	0.428	0.529	0.405	0.488	0.446
CPR2	0.363	0.355	0.407	**0.774**	0.414	0.418	0.408	0.409	0.521	0.422	0.491	0.427	0.515	0.412	0.462	0.42
CPTE3	0.383	0.328	0.406	**0.766**	0.393	0.401	0.369	0.384	0.52	0.403	0.503	0.436	0.504	0.426	0.477	0.442
EE1	0.462	0.401	0.484	0.41	**0.741**	0.489	0.433	0.454	0.454	0.534	0.489	0.555	0.397	0.531	0.378	0.509
EE2	0.442	0.432	0.502	0.433	**0.792**	0.529	0.476	0.485	0.453	0.547	0.531	0.573	0.41	0.515	0.377	0.479
EE3	0.3	0.413	0.368	0.327	**0.633**	0.472	0.411	0.388	0.354	0.42	0.389	0.463	0.333	0.353	0.257	0.331
EE4	0.434	0.445	0.486	0.434	**0.814**	0.56	0.496	0.488	0.464	0.533	0.513	0.571	0.409	0.502	0.357	0.454
EE5	0.433	0.443	0.5	0.423	**0.8**	0.557	0.503	0.507	0.459	0.532	0.514	0.611	0.417	0.511	0.363	0.473
FC1	0.354	0.511	0.429	0.377	0.521	**0.776**	0.51	0.472	0.382	0.467	0.455	0.525	0.387	0.443	0.314	0.372
FC2	0.408	0.478	0.468	0.427	0.543	**0.771**	0.529	0.5	0.423	0.495	0.492	0.56	0.394	0.482	0.348	0.444
FC3	0.452	0.393	0.462	0.444	0.515	**0.717**	0.435	0.465	0.448	0.505	0.5	0.567	0.396	0.507	0.382	0.506
FC4	0.359	0.448	0.414	0.4	0.514	**0.792**	0.491	0.47	0.413	0.462	0.451	0.526	0.388	0.449	0.333	0.41
FC5	0.428	0.412	0.444	0.408	0.54	**0.768**	0.484	0.496	0.446	0.487	0.492	0.555	0.382	0.498	0.359	0.461
FC6	0.404	0.486	0.459	0.42	0.548	**0.802**	0.546	0.523	0.454	0.49	0.489	0.548	0.407	0.473	0.343	0.448

	AP	AU	BI	CP	EE	FC	H	HM	LP	PE	SE	SI	SP	SS	TP	TV
H1	0.388	0.49	0.513	0.428	0.543	0.586	**0.882**	0.714	0.454	0.521	0.489	0.545	0.437	0.498	0.347	0.448
H2	0.404	0.497	0.515	0.446	0.546	0.576	**0.898**	0.671	0.454	0.525	0.5	0.552	0.433	0.505	0.349	0.477
H3	0.421	0.464	0.521	0.44	0.527	0.551	**0.86**	0.669	0.45	0.511	0.505	0.562	0.432	0.51	0.355	0.494
HM1	0.4	0.456	0.5	0.433	0.55	0.556	0.674	**0.888**	0.45	0.506	0.497	0.566	0.411	0.506	0.341	0.436
HM2	0.443	0.456	0.532	0.473	0.561	0.573	0.706	**0.902**	0.476	0.544	0.521	0.582	0.453	0.525	0.388	0.473
HM3	0.426	0.455	0.51	0.465	0.533	0.563	0.701	**0.886**	0.448	0.528	0.51	0.568	0.438	0.512	0.365	0.459
LPER1	0.404	0.369	0.414	0.492	0.455	0.447	0.433	0.403	**0.74**	0.441	0.503	0.447	0.473	0.443	0.405	0.44
LPER2	0.379	0.329	0.361	0.478	0.405	0.396	0.371	0.348	**0.727**	0.417	0.49	0.421	0.439	0.393	0.363	0.406
LPER3	0.412	0.35	0.413	0.506	0.434	0.434	0.377	0.372	**0.733**	0.462	0.499	0.448	0.432	0.435	0.394	0.444
LPMSR1	0.401	0.37	0.408	0.511	0.452	0.429	0.414	0.393	**0.756**	0.447	0.512	0.473	0.48	0.421	0.409	0.426
LPMSR2	0.406	0.339	0.395	0.506	0.426	0.413	0.372	0.389	**0.757**	0.442	0.498	0.456	0.458	0.411	0.402	0.446
LPMSR3	0.381	0.353	0.386	0.484	0.428	0.435	0.389	0.396	**0.748**	0.434	0.516	0.473	0.46	0.408	0.393	0.433
LPMSR4	0.408	0.349	0.399	0.487	0.445	0.417	0.383	0.377	**0.753**	0.436	0.524	0.465	0.45	0.415	0.43	0.448
LPMSR5	0.391	0.343	0.396	0.493	0.406	0.398	0.356	0.37	**0.759**	0.424	0.499	0.441	0.457	0.386	0.408	0.433
LPMSR6	0.416	0.347	0.422	0.496	0.432	0.42	0.38	0.38	**0.77**	0.457	0.516	0.47	0.468	0.421	0.398	0.468
LPMSR7	0.413	0.342	0.404	0.494	0.433	0.394	0.38	0.383	**0.769**	0.433	0.516	0.452	0.463	0.41	0.411	0.446
LPMSR8	0.408	0.345	0.418	0.51	0.437	0.402	0.385	0.395	**0.753**	0.456	0.5	0.477	0.464	0.425	0.408	0.448
LPMSR9	0.432	0.354	0.436	0.5	0.438	0.407	0.374	0.378	**0.759**	0.458	0.513	0.471	0.465	0.428	0.42	0.446
LPSEL2	0.411	0.299	0.383	0.486	0.412	0.373	0.364	0.372	**0.707**	0.418	0.486	0.457	0.429	0.433	0.401	0.484

	AP	AU	BI	CP	EE	FC	H	HM	LP	PE	SE	SI	SP	SS	TP	TV
LPSEL3	0.396	0.378	0.413	0.489	0.446	0.44	0.41	0.416	**0.728**	0.424	0.512	0.462	0.466	0.424	0.398	0.46
LPSEL4	0.427	0.313	0.389	0.497	0.428	0.395	0.372	0.378	**0.739**	0.423	0.513	0.456	0.442	0.433	0.418	0.471
ME2	0.438	0.415	0.461	0.482	0.505	0.477	0.457	0.46	0.491	0.533	**0.752**	0.534	0.443	0.495	0.398	0.471
ME3	0.428	0.405	0.46	0.461	0.489	0.475	0.461	0.462	0.48	0.543	**0.747**	0.529	0.445	0.498	0.396	0.461
ME4	0.448	0.394	0.463	0.48	0.488	0.492	0.453	0.46	0.497	0.528	**0.747**	0.531	0.438	0.504	0.418	0.481
PE1	0.438	0.411	0.53	0.425	0.546	0.506	0.464	0.465	0.453	**0.81**	0.537	0.571	0.403	0.52	0.397	0.463
PE2	0.448	0.431	0.513	0.448	0.549	0.508	0.473	0.469	0.476	**0.833**	0.553	0.567	0.422	0.517	0.393	0.471
PE3	0.479	0.408	0.527	0.462	0.565	0.521	0.493	0.508	0.496	**0.838**	0.559	0.577	0.43	0.54	0.424	0.498
PE4	0.462	0.436	0.509	0.473	0.585	0.538	0.518	0.509	0.513	**0.821**	0.57	0.581	0.448	0.536	0.424	0.514
SI1	0.417	0.448	0.474	0.392	0.567	0.534	0.488	0.473	0.439	0.509	0.499	**0.732**	0.394	0.474	0.342	0.485
SI2	0.45	0.427	0.508	0.428	0.581	0.54	0.499	0.49	0.478	0.543	0.55	**0.76**	0.415	0.52	0.377	0.513
SI3	0.471	0.412	0.501	0.421	0.557	0.524	0.469	0.481	0.481	0.543	0.538	**0.778**	0.415	0.544	0.389	0.541
SI4	0.462	0.411	0.501	0.425	0.548	0.543	0.484	0.507	0.473	0.533	0.536	**0.791**	0.414	0.539	0.368	0.519
SI5	0.422	0.428	0.473	0.426	0.551	0.549	0.47	0.482	0.464	0.54	0.523	**0.772**	0.426	0.529	0.362	0.492
SI6	0.464	0.427	0.499	0.433	0.552	0.526	0.477	0.498	0.474	0.538	0.525	**0.778**	0.402	0.549	0.362	0.518
SI7	0.451	0.425	0.464	0.448	0.568	0.561	0.504	0.499	0.47	0.527	0.511	**0.749**	0.417	0.497	0.36	0.495
SI8	0.457	0.436	0.491	0.461	0.569	0.563	0.457	0.497	0.473	0.523	0.53	**0.76**	0.431	0.513	0.379	0.51
SPAE1	0.365	0.329	0.391	0.498	0.39	0.372	0.351	0.358	0.461	0.406	0.454	0.419	**0.709**	0.419	0.48	0.398
SPAE2	0.311	0.343	0.369	0.488	0.387	0.398	0.366	0.355	0.433	0.374	0.433	0.411	**0.734**	0.374	0.434	0.334

	AP	AU	BI	CP	EE	FC	H	HM	LP	PE	SE	SI	SP	SS	TP	TV
SPAE3	0.319	0.302	0.366	0.481	0.38	0.373	0.351	0.346	0.437	0.366	0.414	0.416	**0.739**	0.377	0.465	0.361
SPAE4	0.31	0.328	0.375	0.501	0.407	0.385	0.386	0.382	0.455	0.406	0.443	0.42	**0.764**	0.388	0.448	0.361
SPAE5	0.316	0.339	0.369	0.485	0.404	0.392	0.386	0.379	0.441	0.397	0.422	0.402	**0.77**	0.368	0.458	0.35
SPGC1	0.277	0.344	0.35	0.467	0.369	0.361	0.362	0.35	0.439	0.354	0.399	0.37	**0.712**	0.324	0.393	0.316
SPGC2	0.333	0.344	0.367	0.525	0.408	0.374	0.366	0.36	0.494	0.387	0.449	0.397	**0.758**	0.359	0.451	0.375
SPGC3	0.321	0.338	0.377	0.539	0.387	0.407	0.384	0.379	0.474	0.392	0.444	0.412	**0.764**	0.369	0.455	0.374
SPGC4	0.362	0.354	0.385	0.543	0.403	0.393	0.391	0.401	0.489	0.397	0.468	0.427	**0.764**	0.4	0.459	0.418
SPOC1	0.304	0.342	0.36	0.493	0.397	0.397	0.386	0.385	0.442	0.391	0.433	0.416	**0.774**	0.379	0.453	0.37
SPOC2	0.337	0.315	0.371	0.533	0.405	0.377	0.382	0.377	0.484	0.403	0.451	0.419	**0.785**	0.39	0.474	0.4
SPOC3	0.344	0.353	0.38	0.506	0.395	0.38	0.369	0.361	0.485	0.398	0.443	0.413	**0.795**	0.376	0.452	0.387
SPOC4	0.328	0.332	0.371	0.515	0.381	0.393	0.37	0.358	0.474	0.396	0.43	0.398	**0.766**	0.376	0.464	0.377
SS1	0.494	0.416	0.538	0.394	0.505	0.475	0.464	0.47	0.408	0.539	0.499	0.547	0.368	**0.736**	0.362	0.493
SS2	0.506	0.42	0.518	0.429	0.526	0.518	0.493	0.462	0.459	0.53	0.528	0.535	0.432	**0.787**	0.416	0.524
SS3	0.542	0.355	0.487	0.423	0.473	0.455	0.414	0.417	0.423	0.481	0.509	0.505	0.372	**0.795**	0.359	0.529
SS4	0.569	0.382	0.496	0.431	0.486	0.472	0.411	0.44	0.427	0.484	0.497	0.527	0.366	**0.796**	0.392	0.552
SS5	0.548	0.411	0.501	0.433	0.504	0.503	0.449	0.469	0.463	0.47	0.489	0.524	0.405	**0.777**	0.396	0.528
SS6	0.539	0.408	0.523	0.431	0.496	0.445	0.439	0.431	0.435	0.477	0.474	0.539	0.381	**0.772**	0.36	0.533
TPDI1	0.351	0.234	0.318	0.471	0.331	0.323	0.292	0.315	0.431	0.37	0.41	0.368	0.433	0.363	**0.758**	0.4
TPDI2	0.32	0.248	0.32	0.468	0.333	0.33	0.311	0.318	0.422	0.362	0.401	0.35	0.457	0.353	**0.751**	0.382

	AP	AU	BI	CP	EE	FC	H	HM	LP	PE	SE	SI	SP	SS	TP	TV
TPDI3	0.342	0.266	0.352	0.477	0.356	0.347	0.322	0.33	0.415	0.38	0.398	0.36	0.457	0.38	**0.742**	0.388
TPDO1	0.313	0.24	0.323	0.419	0.323	0.312	0.277	0.286	0.373	0.368	0.361	0.341	0.422	0.37	**0.701**	0.346
TPDO2	0.358	0.214	0.31	0.406	0.325	0.318	0.265	0.281	0.384	0.368	0.391	0.347	0.412	0.367	**0.725**	0.367
TPDO3	0.343	0.265	0.344	0.432	0.344	0.325	0.277	0.282	0.382	0.382	0.381	0.358	0.428	0.361	**0.73**	0.389
TPDO4	0.335	0.269	0.318	0.416	0.33	0.323	0.269	0.297	0.369	0.353	0.377	0.343	0.427	0.346	**0.721**	0.346
TPF1	0.325	0.287	0.331	0.457	0.357	0.354	0.298	0.303	0.398	0.367	0.399	0.356	0.451	0.36	**0.739**	0.36
TPF2	0.346	0.269	0.326	0.449	0.358	0.339	0.312	0.294	0.396	0.373	0.412	0.364	0.449	0.369	**0.769**	0.383
TPF3	0.316	0.276	0.32	0.462	0.34	0.331	0.296	0.291	0.395	0.354	0.402	0.347	0.467	0.367	**0.766**	0.355
TPF4	0.356	0.283	0.344	0.487	0.344	0.348	0.293	0.307	0.426	0.376	0.408	0.373	0.462	0.382	**0.772**	0.376
TPF5	0.331	0.257	0.354	0.475	0.35	0.329	0.31	0.319	0.416	0.379	0.411	0.37	0.444	0.376	**0.752**	0.375
TPF6	0.353	0.309	0.354	0.483	0.366	0.36	0.328	0.34	0.425	0.373	0.425	0.369	0.484	0.357	**0.754**	0.382
TV1	0.487	0.37	0.47	0.416	0.469	0.448	0.445	0.403	0.463	0.458	0.5	0.513	0.389	0.53	0.41	**0.755**
TV2	0.486	0.352	0.459	0.43	0.476	0.451	0.434	0.415	0.475	0.465	0.491	0.519	0.382	0.512	0.38	**0.786**
TV3	0.523	0.381	0.473	0.437	0.478	0.462	0.431	0.42	0.475	0.484	0.518	0.537	0.385	0.555	0.396	**0.82**
TV4	0.5	0.345	0.463	0.437	0.471	0.448	0.426	0.403	0.489	0.467	0.497	0.536	0.4	0.536	0.4	**0.807**
TV5	0.527	0.373	0.489	0.465	0.497	0.478	0.427	0.421	0.497	0.481	0.525	0.563	0.406	0.562	0.42	**0.817**
TV6	0.517	0.344	0.483	0.453	0.47	0.441	0.415	0.392	0.468	0.471	0.494	0.52	0.391	0.549	0.394	**0.808**

7.3.2.2 Criteria of Fornell and Larcker

Based on this particular criterion, it is required that the correlation between a construct and other constructs should have values smaller than the square root of the average variance extracted by the construct. The Pearson correlation refers to the correlation coefficient that quantifies the relationship between the relevant item indicators in this measurement. According to Fornell and Larcker's criterion, establishing discriminant validity is contingent upon fulfilling a specified condition. The researcher conducted an additional evaluation of the instrument's discriminant validity using the Fornell-Larker criterion, as presented in Table 7-3. According to Yeboah (2020), the square root of the average variance extracted (AVE) for each construct, as indicated in the main diagonal, is anticipated to exceed the corresponding values in the vertical direction. The data presented in Table 7-3 indicate that the measurement model successfully meets the Fornell-Larker criterion.

7.3.2.3 Heterotrait-Monotrait (HTMT) ratio of correlation

The Heterotrait-Monotrait Ratio of Correlations (HTMT) is a metric utilised to evaluate the discriminant validity within the context of structural equation modelling (SEM) employing the partial least squares (PLS) approach (Henseler et al., 2015). The HTMT is grounded in the multitrait-multimethod matrix framework, which involves the examination of correlations between indicators of distinct constructs (heterotrait) and correlations between indicators of the same construct (monotrait) (Henseler et al., 2015). The HTMT is computed by dividing the mean of the heterotrait correlations and dividing it by the mean of the monotrait correlations, as Henseler et al. (2015) described.

The HTMT method offers certain benefits compared to alternative ways of evaluating discriminant validity, such as the Fornell-Larcker criterion and cross-loading analysis. The HTMT method does not assume tau-equivalent measurement models, which are improbable to be applicable in most empirical research endeavours (Henseler et al., 2015). Tau-equivalent measurement models assume that all the items or indicators of a concept have the same true score but different error variances (Danner, 2016). The real value of the thing that the item is trying to measure is the true score. Error variance is the random noise or variation that changes the measurement of a thing. Some people might need clarification on the question, have different expectations, or be affected by things outside the survey. These things can make the measurement of an item different from its real score. This means the items measure the same thing with the same accuracy but have different amounts of chance error.

Nevertheless, this is a strong claim that most empirical studies cannot support because different items usually have different true scores and error variances (Schweizer, 2012). Some indicators may be more complicated or straightforward than others, while others may be more important or special. Because of these things, the items may measure different parts of the construct, making the real scores different. So, the HTMT criterion does not rely on this assumption, instead accepting that different true scores on different items as long as they are highly correlated (Freese, nd). This means that the items do not have to measure precisely the same thing but should measure something close enough to represent the same construct.

The HTMT measure proposed by Henseler et al. (2015) offers a more straightforward and intuitive approach to assessing discriminant validity. It accomplishes this by comparing the magnitude of relationships between constructs with the magnitude of relationships within constructs. According to Ringle et al. (2022), when the HTMT value falls below 0.90, it indicates the presence of discriminant validity between two constructs. The inference can be made that an HTMT value exceeding 0.90 indicates a deficiency in discriminant validity. However, it is recommended that researchers employ a threshold of 0.85 for the HTMT when there are substantial differences in the path model structures in terms of conceptualization (Henseler et al., 2015). In accordance with the cut off value of 0.90 for the Heterotrait-Monotrait (HTMT) ratio defined by Henseler et al. (2015), the values shown in Table 7-4 are statistically significant.

The HTMT values found for the constructs show that each construct in the model differed enough from the others and measured different characteristics. So, the measuring model could tell the difference between the two groups. Consequently, the measuring model successfully demonstrated discriminant validity.

Table 7-3: Discriminant Validity using Fornell-Larcker Criterion for constructs.

	P	U	I	P	E	C		M	P	E	E	I	P	S	P	V
P	0.825															
U	.445	.834														
I	.600	.630	.809													
P	.486	.437	.526	.780												
E	.551	.561	.621	.537	.759											
C	.519	.591	.578	.535	.687	.772										
	.459	.550	.587	.498	.612	.649	.880									
M	.475	.511	.576	.513	.614	.632	.778	.892								
P	.543	.463	.539	.663	.578	.554	.514	.514	.747							

E	.553	.511	.630	.547	.679	.628	.590	.591	.587	.826						
E	.588	.518	.588	.634	.646	.622	.566	.571	.679	.672	.739					
I	.587	.557	.639	.561	.734	.708	.628	.642	.613	.695	.688	.765				
P	.431	.444	.491	.669	.520	.509	.493	.487	.611	.516	.578	.541	.757			
S	.685	.513	.657	.545	.641	.616	.573	.577	.561	.640	.643	.681	.499	.777		
P	.453	.353	.446	.610	.460	.448	.398	.410	.541	.496	.535	.480	.599	.490	.745	
V	.634	.452	.592	.551	.597	.569	.537	.512	.598	.589	.631	.665	.491	.677	.501	.799

Table 7-4: Discriminant Validity using HTMT Criterion for Constructs

	AP	**AU**	**BI**	**CP**	**EE**	**FC**	**H**	**HM**	**LP**	**PE**	**SE**	**SI**	**SP**	**SS**	**TP**	**TV**
AP																
AU	0.521															
BI	0.701	0.730														
CP	0.552	0.493	0.590													

EE	0.660	0.676	0.736	0.619											
FC	0.608	0.687	0.668	0.601	0.821										
H	0.541	0.644	0.681	0.562	0.735	0.754									
HM	0.553	0.591	0.663	0.572	0.728	0.729	0.901								
LP	0.609	0.514	0.595	0.712	0.658	0.614	0.573	0.566							
PE	0.655	0.600	0.736	0.621	0.818	0.736	0.695	0.688	0.658						
SE	0.690	0.602	0.679	0.711	0.769	0.721	0.658	0.658	0.753	0.787					
SI	0.674	0.635	0.723	0.617	0.857	0.805	0.717	0.725	0.666	0.798	0.781				
SP	0.484	0.496	0.545	0.720	0.595	0.565	0.551	0.538	0.650	0.579	0.642	0.589			
SS	0.801	0.594	0.756	0.609	0.758	0.711	0.665	0.663	0.620	0.747	0.742	0.770	0.551		
TP	0.511	0.394	0.496	0.658	0.525	0.500	0.446	0.453	0.576	0.559	0.596	0.524	0.639	0.544	
TV	0.733	0.517	0.675	0.609	0.698	0.652	0.618	0.582	0.654	0.681	0.722	0.745	0.537	0.772	0.551

Table 7-5: Variance inflation values

	AP	**AU**	**BI**	**CP**	**EE**	**FC**	**H**	**HM**	**LP**	**PE**	**SE**	**SI**	**SP**	**SS**	**TP**	**TV**
AP																
AU											1.603					
BI		2.017														
CP											2.401					
EE			2.559													

FC		2.209	2.932													
H		1.874	2.789													
HM			2.784													
LP											2.445					
PE			2.523													
SE	1.000												1.000	1.000		
SI			2.537													
SP																
SS																
TP											1.999					
TV			2.063													

7.4 Multicollinearity

When two independent predictors are highly correlated, a problem known as collinearity arises (CFI Team, 2022). Collinearity means that two predictors are linked linearly (Kim, 2019). Multicollinearity is a problem in multiple linear regression models when two or more independent variables (predictors) are highly correlated, meaning that the predictors can make accurate linear predictions about one from the other (Kim, 2019). This can make it hard for regression models to work, such as:

- Small changes in the data or how the model is set up can cause the expected regression coefficients to change unpredictably (CFI Team, 2022).
- The standard errors of the coefficients may get more prominent, making it harder to test whether they are important or make confidence ranges (CFI Team, 2022).
- The model's overall fit may be deceiving because the R-squared number may be high, even if some variables are irrelevant or duplicates (Frost,2022).
- The factors may be hard to understand because it might not be clear which variable caused the effect on the dependent variable (Frost,2022).

In regression analysis, looking for and dealing with multicollinearity is important. There are a few ways to do this, and condition indices and variance inflation factors (VIFs) are two of them (Lindner et al., 2020). Multicollinearity exists when the VIF is above 5-10, or the condition indices are 10-30 (Kim, 2019). There are several approaches to deal with multicollinearity, such as a) deleting one or more independent variables from the fit, b) performing a main components regression, and c) removing variables having strong partial correlations with other variables (Lindner et al., 2020). There is no clear-cut way to tell if multicollinearity is a problem since different cases may require different levels of precision and accuracy. However, a popular way to find multicollinearity is to look at the correlation matrix of the independent variables and look for high correlation coefficients (usually above 0.8 or 0.9) (Frost, 2019). This study shall concentrate on VIF since it is one of the quality criteria reported by SmartPLS. Regarding VIF, Feldman (2018) suggested these general rules of thumb:

- There is no multicollinearity among the factors if VIF = 1.
- There is moderate multicollinearity if 1 < VIF < 5.
- There is high multicollinearity, indicating much overlap if VIF >= 5.

The VIF of the model is shown in Table 7-5. The highest VIF number in the table is 2.932, which is below the standard threshold of 5 for finding high multicollinearity. This shows that there is no big problem with the model's constructs being too similar. The lowest VIF number in the table is 1.000, which means no multicollinearity between E and SP. This means that E and SP are two different constructs that do not have any shared variance.

7.5 Model fit

The model fit in structural equation modelling is essential to hypothesis testing. According to Hair et al. (2019), model fit evaluates how well the hypothesised model matches data trends of variable relationships. In complex models with many factors, model fit evaluation is crucial. According to Kock (2015), it is recommended to employ fit metrics for the evaluation of intricate models, such as the one utilised in this study, prior to engaging in structural equation modelling. The model fit measures the extent to which the model corresponds to the observed data and signifies the statistical significance of the proposed relationships among the variables in the model. The degree of agreement between the proposed model and the empirical data is known as "model fit". The importance of model fit becomes even more pronounced when evaluating hypotheses using a model that includes 144 Likert scale items, as is the case in this study. Thus, model fit is needed for this study due to the model's increased complexity. Assuming that the model fit measures suggest a lack of adequate fit between the model and the data. In this scenario, it is possible to infer that the hypothesised relationships between the variables in the model do not exhibit statistical significance. Because of this, it is essential to check the model fit before interpreting the findings of the hypothesis testing. This entails evaluating the model's goodness of fit using the proper model fit metrics and making any necessary modifications to the model to enhance fit. By doing this, researchers can increase their trust in the model's dependability and validity as well as the precision of the outcomes of the hypothesis testing. A poorly fitting model may lead to erroneous conclusions or incorrect parameter estimates, impacting the validity of the tested hypotheses. Therefore, it is vital to assess model fit using multiple fit indices and to ensure that the model adequately fits the observed data before proceeding with hypothesis testing. In addition, it is advisable to contemplate utilising dimensionality reduction methodologies, such as principal component analysis (PCA) or partial least squares (PLS) regression, to diminish the number of items or inquiries incorporated within the model. This can help to improve model fit and reduce the computational burden associated with testing hypotheses with many items or questions.

Model fit can be assessed using multiple fit indices with different features (Hair et al., 2019; Hu & Bentler, 1999; Kock, 2015). Tabachenik and Fidel (2012) advised SmartPLS model fit to avoid incorrect inferences from poorly fitting models. Hair et al. (2017) propose that a model fit's adequacy can be evaluated by utilising various fit statistics. The chi-square statistic, the goodness-of-fit index (GFI), the adjusted goodness-of-fit index (AGFI), the normed fit index (NFI), the comparative fit index (CFI), and the root-mean-square error of approximation (RMSEA) are all included in this group of fit statistics. The fit statistics presented herein offer insights into how the model aligns with the data, with higher values indicating a more robust fit between the model and the data. The model fit's statistics for the study are shown in Table 7-6.

Table 7-6: Model fit statistics for the model

Criteria	Saturated model	Estimated model
SRMR	0.028	0.065
d_ULS	4.914	26.364
d_G	1.455	1.696
Chi-square	24631.969	27176.749
NFI	0.879	0.867

In the ensuing paragraph, the fit statistics for the study's model shown in Table 7-6. are explained and interpreted. The ideal model that represents a perfect fit for the data is the saturated model. The estimated model approximates the actual model, which is being tested for fit with the collected data. The model fit is computed by comparing the estimated model to the saturated model, using fit statistics with a degree of discrepancy; smaller fit numbers indicate better model fit.

Standardised Root Mean Square Residual (SRMR): The SRMR value shows the average difference between the correlations that have been seen and those that have been expected. Generally, a model fit is considered good if the number is less than 0.08 (Hu & Bentler, 1999). The SRMR for the predicted model is 0.065, which implies that it fits well. (Hu & Bentler, 1999; Kline, 2011).

The squared Euclidean distance *(i.e.,* d_ULS) and the geodesic distance (*i.e.*, d_G) are two ways to determine this difference.

d_ULS: The unweighted least squares model fit is measured by the d_ULS number. It shows the gap between the predicted or estimated model's chi-square value and the saturated model's chi-square value. The value of d_ULS can be used to compare how well different models fit, with smaller values showing a better fit. In Table 7-6 , the estimated model has a d_ULS value of 26.364, which is higher than the saturated model's value of 4.914. This result signifies that the estimated model does not fit as well as the saturated model (Joreskog & Sorbom, 1981; Byrne, 2016).

d_G: The d_G number measures how well the model fits the data. It shows the gap between the estimated model's G-square value and the saturated model's G-square value. Hatcher and O'Rourke (2013) say that a fit should be at least 3 to be considered good. In Table 7-6, the d_G number of the estimated model is 1.696, which is below the threshold and shows that the model fits well (Bentler & Bonett, 1980; Marsh, Hau, & Wen, 2004).

Chi-square: The chi-square test compares the measured covariance matrix (seen) to the covariance matrix that the model predicts (expected). A non-significant chi-square value shows a good fit, but this test is sensitive to the group size and may not always be accurate. However, it depends on the sample size and is often inflated when there are many samples. Therefore, it is best to use other fit measures, like the SRMR and d_G, to measure how well a model fits. In Table 7-6 the chi-square value for the predicted model is 27176.749, which is higher than the chi-square value for the saturated model, which is 24631.969. The estimated model's chi-square value is 27176.749, likely significant because the sample size is enormous (2875) and the model is complicated (Bollen, 1989; Kline, 2011).

Normed Fit Index (NFI): The NFI is a way to measure how much better the fit of the estimated model is than the fit of the null model. Values closer to 1 mean a better fit; however, a fit must be better than 0.9 to be considered good (Bentler & Bonett, 1980). From Table 7-6 the predicted model has an NFI value of 0.867, which is below the threshold Bentler and Bonett specified (1980). But some Authors also consider numbers like 0.828 to be marginally acceptable (Gupta, 2015; Hair et al., 2006). Thus, the NFI value of 0.867 fits well for the model due to its complexity (17 constructs and 144 item indicators) and the huge sample size of 2875 samples (Marsh et al., 2004).

Based on the fit statistics discussed, some areas of the model could be improved. However, the model fit is generally acceptable, and fits the data well. The SRMR, d_ULS, and d_G numbers show that the model fits well in terms of the residuals. The NFI value indicates that the model fits well in terms of the structure as a whole. Even though the Chi-square number is less reliable because it depends on the sample size, it still shows that the model is a good fit. The results show that the model represents the data well and can be used to test the hypotheses or answer the study questions.

7.6 Summary

The approach known as Partial Least Squares Structural Equation Modelling (PLS-SEM) was used in SmartPLS version 4.0.8.1 to conduct further analysis on the study's obtained data. Several critical analyses were conducted to evaluate the study's measuring model. First, the study looked at how well indicators work together and separately to determine the reliability of the overall system. Second, the arithmetic mean of the retrieved variance was used to evaluate convergent validity. Third, the HTMT and the Fornell-Larcker criterion were used to assess discriminant validity. Fourth, item cross-loadings were examined as part of the measurement model assessment. All the indicators included in the model demonstrated satisfactory levels of internal consistency reliability, as indicated by meeting the established thresholds for Cronbach's alpha, composite reliability, and reliability coefficient. These indicators also exhibited acceptable levels of convergent validity, as evidenced by their outer loadings and the average variance extracted. Discriminant validity criteria were also met accordingly: Fornell and Larcker's criteria, Cross loadings, HTMT ratio of correlation and VIF for all the constructs. SRMR, d_G and NFI met the cut-off point while d_ULS and chi-square did not; however, the model was deemed it because of the huge sample size. Thus, the model represents the data well, and can be used to test the hypotheses or answer the study questions. Chapter 9 will give structural model results and consequences, illuminating study links and conclusions.

CHAPTER 8: PRESENTATION OF STRUCTURAL MODEL RESULTS AND DISCUSSION

8.1 Introduction

This chapter discusses the structural model resulting from PLS-SEM analysis. The discussion is centred on testing the hypotheses stated for this study. Section 8.2 recaps the aim and objectives of the study. Section 8.3 is concerned with the criterion for assessing hypotheses. Sections 8.4-8.8 concentrate on each of the objectives stated in 8.2. The importance-Performance MAP Analysis is highlighted in section 8.9. Finally, a summary of the chapter is done in section 8.10.

8.2 Aim and objectives of the study

The study's main aim was to evaluate how students' use and engagement in blended MOOCs will affect their satisfaction and perceived academic performance. The main research question was "how do students' use and engagement with blended MOOCs influence their satisfaction and perceived academic performance"? In order to achieve the main above, specific objectives and questions were stated in Chapter 1. The hypotheses drawn directly from said objectives are listed in this section. The data collected were subjected to rigorous quality criteria specified by the SmartPLS v4 measurement model assessment indicated in Chapter 7. The final structure model is depicted in Figure 8-1 , and the hypotheses testing was based on it. In the diagram, the default blue colour for the overall endogenous constructs–students' satisfaction and perceived academic performance (AP) was changed to red for distinguishing purposes. All the other constructs maintained the blue colour.

8.3 The criterion for assessing Hypotheses

In order to address the research inquiry, which suggests that the adoption and utilisation of blended MOOCs have a positive impact on students' engagement, satisfaction, and academic performance, a specific set of factors was taken into consideration and structural equation modelling (SEM) techniques were employed to conduct hypothesis testing. The evaluation was conducted using various metrics, including standardised path coefficient weights (β), t-values, significance levels (p-values), and squared multiple correlations (SMC or R2) for the dependent variables. Presented below is a concise depiction of the subject matter at hand.

8.3.1 R-squared

R squared, or the coefficient of determination, measures how well a model fits the data by showing what fraction of the total variation in a dependent variable can be attributed to the model's set of independent variables. R-squared can be anywhere from 0 to 1, with 1 signifying that all possible variations in the endogenous construct have been accounted for by the model. Although a high value of R-squared is considered favourable, it should not be assumed that the model is inherently suitable for the data or that the relationships within the model are causal, implying a cause-and-effect connection between variables or changes in one variable leading to changes in another variable. Various authors have classified R-squares into different categories. As an illustration, Cohen (1988) also proposed R2 values to assess the strength of endogenous latent variables, categorising them as substantial (0.26), moderate (0.13), and weak (0.02). Falk and Miller (1992) proposed a minimum threshold of 0.10 for the coefficient of determination (R2). Additionally, Chin (1998) proposed that the R2 values for endogenous latent variables can be categorised as follows: 0.67 (indicating a substantial relationship), 0.33 (indicating a moderate relationship), and 0.19 (indicating a weak relationship).

8.3.2 Path coefficients

The standardised path coefficients indicate the strength and direction of the relationships between variables in a structural equation model (Hair et al., 2017). Beta weights (β) or standardised coefficients are path coefficients. They are standardised or normalised to a mean of zero and a standard deviation of one to simplify factor comparison (Hair et al., 2017, Sarstedt et al., 2021). Path coefficients can be positive or negative. The independent and dependent variables rise together if the path coefficient is positive. As the independent variable rises, the dependent variable falls when the path coefficient is negative. The path coefficient shows how strongly two elements are linked. Stronger links have more significant absolute path coefficients (Hair et al., 2017, Sarstedt et al., 2021). Path coefficients are -1 to +1. Path coefficients are used to test hypotheses regarding variable relationships. T-tests can determine if path values are statistically significant. A path coefficient's p-value under 0.05 is significant (Hair et al., 2017, Sarstedt et al., 2021). Path coefficients can also measure the effect of two factors, just as f-square. For beta coefficient (β), Cohen's guidelines effects are as follows:-Small effect: $|\beta| >= 0.10$, Medium effect: $|\beta| >= 0.30$, and large effect: $|\beta| >= 0.50$ (Cohen,1988). The f-squared can be calculated from the path coefficient: the f-squared number given by squaring the path coefficient and dividing by one minus the squared path coefficient.

8.3.3 F-square

The f-square is symbolised by f^2 or f2. F-square measures how much an exogenous variable impacts an endogenous variable after considering all other exogenous components in the model (Hair et al., 2017, Sarstedt et al., 2021). It shows how each variable contributes to the model. Generally, a more significant effect size represents a stronger association between two variables. In contrast, a smaller effect size shows a weaker relationship. The main objective of the effect size is to assess the magnitude of an external construct's impact on the R2 value of an internal latent variable (Hair et al., 2017). Different guidelines for the effect size exist. Kline (2015) states that an effect size of less than 0.1 is considered small, between 0.1 and 0.5 is considered medium, and greater than 0.5 is considered significant. Again, Cohen (1988 as cited in Hair et al., 2017) provided a guideline for f2's effect size for exogenous constructs on an endogenous construct is modest or small (f2>=0.02), medium or moderate (f2>=0.15), or large (f2>=0.35). The inference of a lack of effect can be made when the effect size values are less than 0.02.

8.3.4 Confidence intervals

A confidence interval indicates a range of plausible values likely to include a population parameter's true value or the population parameter of interest. The confidence level is often set at 95%, indicating the genuine population parameter if the study is repeated multiple times. 2.5% and 97.5% confidence intervals define the range of values likely to include the genuine population parameter with 95% confidence. Confidence intervals let us assess the significance and robustness of our findings. The confidence interval can estimate the population parameter of interest, such as the population mean or population proportion (the percentage of observation with a given characteristic or attribute). It shows the estimate's precision and uncertainty. Hypothesis testing uses confidence intervals to reject null hypotheses. The null hypothesis may be confidently rejected when it falls outside the bounds of the confidence interval. Assuming that the confidence intervals do not encompass the value of zero, it can be inferred that the association between the variables is deemed statistically significant. This outcome furnishes evidence in favour of the alternative hypothesis. Suppose the confidence intervals encompass the value of zero. In that case, it implies that there may not be a statistically significant relationship between the variables. Consequently, additional investigation may be necessary to ascertain the nature of the relationship. SmartPLS provides confidence intervals for the means of the original sample (O) and the re-sample (M). The observed data is denoted as O, while M represents the sample mean of the re-sampled data. The confidence intervals estimate the plausible range of values for the actual population mean of the association between AU and SE. Based on the observed sample mean and standard deviation, confidence intervals establish a range of values within which the true population mean is expected to lie.

8.3.5 T-statistics

The t-statistics, also known as the t-value or critical ratio (CR), indicate the statistical significance of path coefficients. The shape of the t distribution is contingent upon the degrees of freedom (df). Consequently, as the degrees of freedom increase, the t distributions closely resemble a standard normal distribution. In the context of standard normal distribution, values of z less than -1.96 and more excellent than 1.96 serve as the critical thresholds for determining statistical significance, assuming a significance level (α) of 0.05. Hence, when the sample size is sufficiently large, it is possible to assert that a t-value is statistically significant if its absolute value is greater than or equal to 1.96, denoted as $|t|\geq 1.96$. According to Byrne (2016), the path coefficient is considered statistically significant when the t-value exceeds 1.96 in a two-tailed test with a significance level of 0.05. Conversely, if the t-value falls below this threshold, the path coefficient is deemed statistically insignificant and is rejected. In the present study, the sample size comprises 2875 participants, resulting in a corresponding degree of freedom of 2873. Consequently, the null hypothesis will be rejected when the absolute value of t is greater than or equal to 1.96.

8.3.6 P-values

P-values indicate chance probability. Hypothesis testing uses a null hypothesis (no difference) and an alternative hypothesis (different). P-value is a number between 0 and 1 that decides whether or not the null hypothesis is true. A small p-value (usually less than 0.05) makes the data unlikely to be random, thus, supporting our alternative hypothesis. P-values help to decide whether to trust the alternative or null hypothesis by determining if the data are significant or random. Rejecting the null hypothesis does not necessarily entail an automatic acceptance or endorsement of the alternative hypothesis. Instead, it posits that the null hypothesis is invalid, and that the alternative hypothesis may provide a plausible explanation for the observed data. According to the findings of this study, a p-value that falls below the threshold of 0.05 is deemed statistically significant.

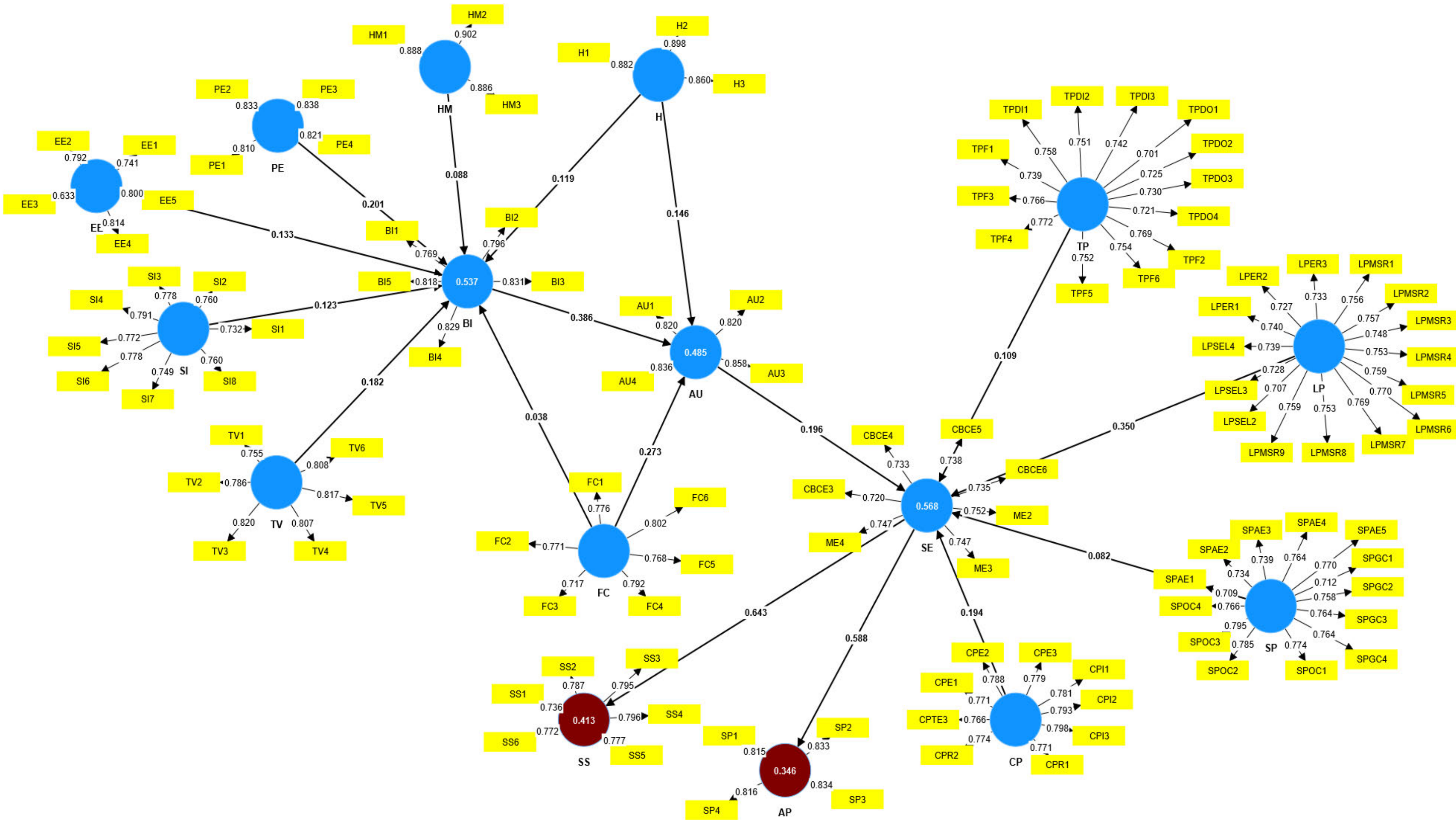

Figure 8-1.Impact of Blended MOOCs Use and Student Engagement on Satisfaction and Academic Performance

Table 8-1: Hypotheses Test

Null Hypotheses (H0)	Relationship	Original sample (O)	T-value	P-value	F^2	Confidence Interval		Decision for Hypotheses	H0. Test Results
						LB 2.5%	UB 97.5%		
There are no determinants that influence learners' willingness to use blended MOOCs in the future.	EE -> BI	0.133	4.151	0.000	0.014	0.069	0.195	Rejected	Rejected
	FC -> BI	0.038	1.232	0.218	0.001	-0.021	0.098	**Retained**	
	H -> BI	0.119	4.016	0.002	0.010	0.061	0.174	Rejected	
	HM -> BI	0.088	3.040	0.000	0.006	0.032	0.144	Rejected	
	PE -> BI	0.201	7.082	0.000	0.037	0.145	0.257	Rejected	
	SI -> BI	0.123	3.772	0.000	0.010	0.059	0.188	Rejected	
	TV -> BI	0.182	7.655	0.000	0.036	0.136	0.231	Rejected	
There are no factors that influence learners' adoption and sustained use of blended MOOCs.	BI -> AU	0.386	15.127	0.000	0.170	0.337	0.437	Rejected	Rejected
	FC -> AU	0.273	10.065	0.000	0.075	0.219	0.326	Rejected	
	H -> AU	0.146	5.679	0.000	0.021	0.095	0.195	Rejected	
The presence of community inquiry has no impact on blended MOOCs' engagement.	CP -> SE	0.194	7.140	0.000	0.036	0.141	0.247	Rejected	Rejected
	LP -> SE	0.350	13.040	0.000	0.136	0.299	0.403	Rejected	
	SP -> SE	0.082	3.595	0.000	0.007	0.039	0.128	Rejected	
	TP -> SE	0.109	5.574	0.000	0.015	0.072	0.149	Rejected	
There is no relationship between students' engagement and satisfaction in blended MOOCs.	SE -> SS	0.643	35.437	0.000	0.704	0.606	0.678	Rejected	Rejected
There is no relationship between students' engagement and perceived academic performance in blended MOOCs.	SE -> AP	0.588	30.751	0.000	0.529	0.551	0.625	Rejected	Rejected
Students' actual use of blended MOOCs does not influence their engagement.	AU -> SE	0.196	10.106	0.000	0.065	0.158	0.234	Rejected	Rejected

8.4 Assessing students' actual use of the blended MOOC system

Many factors are antecedent to the actual use of technology, like blended MOOCs. Venkatesh et al. (2003) and Venkatesh et al. (2012) list several of them, which form the basis of the hypotheses the researcher shall discuss in this section. The hypothesis under consideration is:

H1: These factors (PE, EE, SI, FC, H, HM and TV) of UTAUT will positively influence students' Intention (BI) to use blended MOOCs.

This assertion is supported by H1a, H1b, H1c, H1d, H1e, H1f and H1g.

8.4.1 Factors affecting behavioural intention to use technology

Behavioural intention deals with how a person plans to do or not do a specific behaviour. Students must be motivated to decide to use blended MOOCs for learning. Some factors must facilitate this behaviour (Venkatesh et al., 2003; Venkatesh et al. (2012), which the section considers.

8.4.1.1 Performance Expectancy and intention to use

H1a: Performance Expectancy (PE) will positively influence students' intention (BI) to use the blended MOOC system.

Hypothesis H1a is essential to test because it asserts whether or not the blended MOOC system will help students to learn or do better in some way. Thus, testing the hypothesis is essential if researchers want to know what makes students use and accept the method. There is both theory and empirical support for the idea that users' expectations of how technology will work, including blended MOOC systems, affect their plans to use it and that the UTAUT model helps to understand how people accept and use technology. (Venkatesh et al., 2003; Venkatesh et al., 2012). Again, a study of 174 papers by UTAUT showed that the relationship between PE and BI was significant in 93 of 116 cases, giving it a predictive weight of 0.80. (Williams et al., 2015).

The statistics for the relationship between PE and BI are *β=0.201, t (2872) = 7.082, p=0.000, f2= 0.037, CI (0.145, 0.257)*. These statistics ($p<0.05$ and $t > 1.96$ for α =0.05) show that the null hypothesis should be rejected since performance expectancy influences behavioural intention. This p-value means a relationship exists between BI, and that there is less than a 5% chance that this relationship happened by chance. Again, PE has a path coefficient (β) of 0.201, indicating a moderate and positive link between performance expectancy and behavioural intention in blended MOOCs. This finding aligns with earlier research (Venkatesh et al., 2003; Venkatesh et al., 2012) that found a link between performance expectancy and behavioural intention. Furthermore, the t-statistic (which examines how far the sample mean is from the overall mean in terms of standard error) was 7.082, higher than the critical value of 1.96 for α =0.05 at a degree of freedom of 2872. Additionally, the β-value indicates that for each unit increase in behavioural intention, there is a 0.201 unit increase in performance expectancy. Based on the data, performance expectancy is an essential factor affecting behavioural intention in blended MOOCs. The f-square value is 0.037, which indicates that the effect size of PE on BI is slightly moderate (Cohen, 1988 as cited in Hair et al., 2017) and also that PE explains 14.5% of the variance of BI. The confidence intervals (2.5%) and (97.5%) are 0.145 and 0.257, respectively. These values indicate the range of values within which the true population parameter for the relationship between PE and BI will likely fall with 95% confidence. Specifically, the study can be 95% confident that the true population parameter lies between 0.145 and 0.257.

8.4.1.2 Effort Expectancy and intention to use

> *H1b: Effort Expectancy (EE) will positively influence students' intention to use (BI) the blended MOOC System.*

Hypothesis H1b is essential to test because it talks about how easy or hard it is for students to use the blended MOOC system and how that changes their plans to use it. Users' expectations of how hard it will be to use technology are vital to whether or not they will use it. Users' perceptions of how easy it is to use can tell a lot about their attitudes and actions towards technology. Testing the idea that students will be more likely to use the blended MOOC system if they think they will have to put in more work is essential to know what makes students accept and use the system. The UTAUT model helps us to understand how people accept and use technology. There is theoretical and empirical support for the value of users' expectations of how much work it will take to use technology, including blended MOOC systems. (Venkatesh et al., 2003; Venkatesh et al., 2012). Again, a study of 174 papers by UTAUT showed that the relationship between EE and BI was significant in 64 of 110 papers, giving it a predictive weight of 0.58. (Williams et al., 2015).

The statistics for the relationship between EE and BI are *β=0.133, t (2872) = 4.151, p=0. 000, f^2= 0.014, CI (0.069, 0.195)*. The statistical analysis shows that there is a significant link between effort expectancy (EE) and behavioural intention (BI) (t (2872) = 4.151> 1.96 for α =0.05, and p< 0.05). The data show a significant relationship between EE and BI among the study participants. The finding shows less than a 5% chance that this relationship happened by chance. Additionally, the β-value indicates that for each unit increase in behavioural intention, there is a 0.133 unit increase in effort expectancy. The results show that students are likelier to use technology if they think it will take little effort to work. The result fits with the UTAUT 2 theory, which indicates that how easy something seems to use is a key factor in deciding whether or not someone will use it (Venkatesh et al., 2003; Venkatesh et al., 2012). The F-square of 0.014 has a negligible effect (Cohen, 1988, as cited in Hair et al., 2017) and indicates that EE explains 1.4% of the variance in BI. The confidence intervals for the relationship between EE and BI are 0.069 and 0.195, respectively. This result denotes that the study can be 95% confident that EE's population parameter (true mean) on BI is between 0.069 and 0.195. Since the confidence interval does not include zero, the study can again conclude that the effect of EE on BI is statistically significant at the 95% confidence level.

8.4.1.3 Social Influence and Behavioural Intention to use

> *H1c: Social Influence (SI) will positively influence the student's intention (BI) to use the blended MOOC system.*

Social influence is a big part of how people accept and use technology. (Li & Zhao, 2021). In the context of this study, H1c claims that students will be more likely to use the blended

MOOC system if their peers influence them. By putting this theory to the test, the study can shed light on the role of social influence in blended MOOCs and help us learn more about what makes people accept and use technology in educational settings. The UTAUT model helps us to understand how people accept and use technology. Theoretical considerations and empirical evidence suggest that social impact is essential in how people use technology, including blended MOOC systems. (Venkatesh et al., 2003; Venkatesh et al., 2012). Again, a study of 174 papers by UTAUT showed that the relationship between BI was significant in 86 of 115 cases, giving it a predictive weight of 0.75. (Williams et al., 2015).

The statistics for the relationship between SI and BI are $\beta=0.123$, $t\ (2872) = 3.772$, $p=0.000$, $f^2 = 0.010$ *and CI (0.059, 0.188)*. The p-value was zero, indicating a relationship between SI and BI. The relationship between social influence SI) and behavioural intention BI) was found to have a path coefficient of 0.123, which shows that the two variables were related positively. The t statistic was 3.772, higher than the critical value of 1.96 for a 95% confidence interval, indicating that the link was significant. The results showed that social influence and behavioural intention were linked in a statistically significant way. This finding is consistent with previous studies, highlighting the role of social influence in determining the intention to use technology (Venkatesh et al., 2003; Venkatesh et al., 2012). This result means that as Social Influence went up, so did the chance that students would act in ways that showed they wanted to be engaged, satisfied and did well in blended MOOCs. The path coefficient of 0.123 means that for every one-unit increase in behavioural intention, there was a 0.123-unit rise in Social Influence. The f^2's effect size of the relationship between SI and BI was 0.010, representing a negligible effect (Cohen, 1988, as cited in Hair et al., 2017). Thus, SI explains only 1% of BI variance, suggesting that other things may also be causing students to be interested in blended MOOCs. The 95% confidence interval (0.059, 0.188) means the study could be 95% confident that the true population mean lay between these two values. This interval did s does not include zero, which is another reason to reject the null hypothesis indicating that the relationship between SI and BI was statistically significant.

8.4.1.4 Facilitating conditions and intention to use

H1d: Facilitating conditions (FC) will positively influence the student's intention (BI) to use the blended MOOC system.

There is theoretical and empirical evidence for the idea that users' intentions to use technology, such as blended MOOC systems, are affected by facilitating conditions and that the UTAUT model is useful for understanding how people accept and use technology. (Venkatesh et al., 2003; Venkatesh et al., 2012). Again, a study of 174 papers on UTAUT found that the relationship between FC and BI was significant in 33 of 48, giving it a predictive weight of 0.69. (Williams et al., 2015). It is essential to try the idea that making EdTech available with the necessary supporting systems will make students more likely to use the blended MOOC system. Such results can help to guide strategies for improving the system's infrastructure and support to get more students to use it. In the case of blended MOOCs, the link is the effect of facilitating conditions FC) on behavioural intention BI).

The statistics for the relationship between FC and BI are $\beta=0.038$, $t = 1.232 < 1.96$ *for* $\alpha=0.05$, $p=0.218$, *CI* $(-0.021, 0.098)$, $f^2= 0.001$. The p-value ($p=0.218 > 0.005$). The path coefficient of FC on BI ($\beta=0.038$) shows that the two variables had a weakly positive link. Furthermore, since the p-value was higher than the significance level of 0.05, the finding was not statistically significant. Thus, the researcher could not reject the null hypothesis that there was no relationship between FC and BI. Even though this finding went against the UTAUT and UTAUT 2 models (Venkatesh et al., 2003; Venkatesh et al., 2012), it aligns with a few views that suggest that facilitating conditions might not be important in determining the intention to use technology in this study scenario. (Guo et al., 2020; Liebenberg et al., 2018; Thomas et al., 2013; Wangdi et al., 2023). The confidence intervals indicate the range of values where the true population mean is likely to lie with a given confidence level. The confidence interval for FC and BI was (-0.021, 0.098) at the 95% confidence level. This CI means that if the study sampled from the population and calculated the confidence intervals repeatedly, it expects that about 95% of these intervals will contain the true population mean. In this case, since the confidence interval includes zero, it further supports the idea that FC and BI have no statistically significant relationship. The F-square value is 0.001, which is a negligible effect of FC on BI (Cohen, 1988, as cited in Hair et al., 2017). The F-square value is 0.001, indicating that FC can explain 0.1% of the variation in BI.

8.4.1.5 Habit and intention to use

H1e: Habit(H) will positively influence the student's intention (BI) to use the blended MOOC system.

Habit is a good predictor of future behaviour and real use when adopting new technologies. Habit is an important thing to keep in mind when studying technology adoption. Venkatesh et al. (2012) said that habits should be a factor in future models of how people accept new technologies. Several studies (Escobar-Rodrguez et al., 2014) have used the habit construct to predict how people use technology. Yu et al. (2021) examined the behaviour desire to use a mobile health education website. They found that habits, among other things, were key predictors. Again, a study by Tak and Panwar (2017) found that hedonic motivation and habit are the most significant predictors of users' behaviour intentions to use mobile apps for shopping. In their study of what makes students in urban and rural areas use tablet computers as learning tools, Wang et al. (2022) found that habit and task technology fit were the most critical factors for university students in urban areas. Because of this, the researcher included H1e in this study. The UTAUT2 model was used by Nasef et al. (2019) to find out how learners felt about MOOCs. They found that habit was the factor that most affected learners' plans to sign up for MOOCs.

The statistics for the relationship between H and BI are $\beta=0.119$, $t = 4.016 > 1.96$ *for* $\alpha=0.05$, $p=0.000$, *CI ((0.061, 0.174), and* $f^2= 0.010$. The p-value ($p<0.05$) indicates that the null hypothesis that H does not affect BI should be rejected as H influences BI. Furthermore, the path coefficient indicates a significant relationship between H and BI. Thus, a significant positive relationship exists between habit (H) and behavioural intention (BI). Moreover, the path coefficient of 0.123 means that for every one-unit increase in behavioural intention, there is a 0.123-unit rise in habit construct. The result suggests that the more students get used to using technology and participating in course activities, the more likely they want to keep doing so. The confidence interval (0.061, 0.174) indicates 95% confidence that the true population parameter for the relationship between H and BI falls within this range. Since the confidence interval does not include zero, it further supports the idea that H and BI have a statistically significant relationship. The F-square value is 0.010, indicating a negligible effect of H on BI (Cohen, 1988, as cited in Hair et al., 2017). It tells us that 1.0 % of the variation in Actual Use (AU) can be explained by Habit (H). This finding is consistent with past investigations, showing the significance of habit in technology use and how habits significantly impact how students act and make decisions. Encouraging students to make habits could be an effective way to make them more interested in and satisfied with blended MOOCs. One way would be to get people to regularly use the technology and course materials accompanied by reminders, prizes and game-like elements. Making technology easy to use and get can also help people to get into the habit of using it.

8.4.1.6 Hedonic Motivation and intention to use

> *H1f: Hedonic Motivation (HM) will positively influence the student's intention (BI) to use the blended MOOC system.*

Studies provide evidence to support the hypothesis that hedonic motivation positively influences students' intention to use technology in education (Venkatesh et al.,2012). H1f suggests that students' enjoyment and pleasure in using the blended MOOC system will positively impact their intention to use it. Venkatesh et al. (2012) discussed the importance of hedonic motivation (enjoyment or fun) in technology acceptance and use, and how it can influence users' attitudes and behaviours towards technology. Again, a study by Tak and Panwar (2017) revealed that hedonic motivation and habit are the strongest predictors of users' behavioural intention to use mobile apps for shopping. Moreover, in identifying the predictors influencing urban and rural students to use tablet computers as learning tools, Wang et al. (2022) discovered that hedonic motivation and task technology fit were the most significant factors for university students in rural areas. Another study by Nasef et al. (2019), analysing MOOC intentions, using the UTAUT2 model, found that hedonic motivation is one of the most significant factors influencing behavioural intention to use MOOCs.

The statistics for the relationship between HM and BI are *β=0.088., t = 3.040 > 1.96 for α =0.05, p=0.002, f2=0.006. CI (0.032, 0.144)*. The t-statistics and p-value of 0.002, below the significance level of 0.05, indicating that the relationship between HM and BI is statistically significant. The t-value indicates the strength and direction of the relationship between HM and BI. In this case, the t-value of the relationship between H and BI is significant and not likely due to chance. The path coefficient is 0.088, which suggests a positive relationship between HM and BI. Thus, the null hypothesis for H1f is rejected, suggesting that hedonic motivation positively affects behavioural intention. The result agrees with prior studies and indicates that hedonic motivation positively impacts behavioural intention. The results again show that students motivated by pleasure, enjoyment and excitement in learning are more likely to intend to engage in blended MOOCs. Finally, the path coefficient of 0.088 means that for every one-unit increase in behavioural intention, there was a 0.088-unit rise in hedonic motivation. The HM-BI relationship was weak, with an effect size of 0.006(Cohen, 1988, as cited in Hair et al., 2017). HM explains only 0.6% of BI variance. This result shows that while HM and BI may be statistically significant, their practical significance was minimal. However, even if its effect size was minor, HM may be relevant to understanding and improving BI. HM and BI may not have a straightforward cause-and-effect relationship. Other variables may interact with or mediate the relationship between HM and BI; removing HM without considering these other factors could have unintended consequences. The confidence interval for the lower bound of the estimate was 0.032, and the upper bound was 0.144. This result infers that the study can be 95% confident that the true population parameter for the relationship between HM and BI falls within this range. In other words, if the sampling is repeated many times, the population parameter would be found within this range in 95% of the cases.

8.4.1.7 Task value and intention to use

H1g: Task value(TV) will positively influence the student's intention (BI) to use the blended MOOC system.

H1g suggests that task value is essential in predicting users’ intention to use technology. Specifically, task value refers to the perceived usefulness of technology in accomplishing a specific task or achieving a goal. Users are more likely to adopt a technology if they perceive it as valuable for accomplishing their goals. Therefore, if H1g is supported, it would indicate that students are more likely to use the blended MOOC system if they perceive it as valuable for achieving their learning goals. This hypothesis is necessary to investigate as it can provide insights into the factors that drive student engagement and adoption of blended MOOC systems. There is theoretical and empirical support for the importance of facilitating conditions in shaping users' intention to use technology, including blended MOOC systems, and for the relevance of the UTAUT model in understanding technology acceptance and use (Venkatesh et al., 2012). Chiu and Wang (2008) examined the factors influencing individuals' intentions to continue engaging in Web-based learning. The researchers found three variables, attainment, utility, and intrinsic value, emerged as significant predictors in this context. The researchers reached the conclusion that the positive subjective task value had a significant impact on learners' intentions to continue, which was equally important as performance expectancy and effort expectancy. Khechine et al. (2020) demonstrated that the intrinsic value construct played a significant role in explaining the behavioural intention to utilise a learning management system incorporating social media technology. The statistics for the relationship between TV and BI are $\beta=0.182$, $t = 7.655 > 1.96$ *for* $\alpha=0.05$, $p=0.000$, *CI (0.136, 0.231),* $f^2= 0.036$. The p-value ($p<0.05$) indicates that the null hypothesis that TV does not affect BI should be rejected as TV influences BI. Furthermore, the path coefficient indicates a significant relationship between TV and BI. Thus, a significant positive relationship exists between habit (H) and behavioural intention (BI). Moreover, the path coefficient of 0.182 means that for every one-unit increase in behavioural intention, there is a corresponding 0.182-unit rise in the task value construct. The confidence intervals (2.5% and 97.5%) for the relationship between TV and BI are 0.136 and 0.231, respectively. Since both intervals do not include zero, the study can say with 95% confidence that the true population parameter lies between these values. This result also indicates a significant relationship between TV and BI. Additionally, the F-square value of 0.036 is small (Cohen, 1988, as cited in Hair et al., 2017), indicating that the variance in TV can explain 3.6% of the variance in BI. The results of this study suggest that task value is an essential factor in influencing students' behavioural intention towards blended MOOCs. Students who perceive greater task value in their studies are more likely to have a positive intention towards engaging with the technology and the course material. Task value refers to how students perceive the course material as meaningful and relevant to their goals and interests. Students who perceive the course material as valuable are likelier to engage with it and perform better. Students who perceive greater value in the tasks assigned in the blended MOOC are more likely to have a positive intention to engage with the course material and complete the assigned tasks. Overall, these results suggest that task value has a significant role in influencing how students experience blended MOOCs and that instructors and course designers should work to emphasise the relevance and importance of the tasks assigned in the course.

Now is the time to return to the objective of H1, which states that no significant factors influence behavioural intention in the study context. Six factors, EE, PE, HM, SI, TV and H, have positive relationships with BI, as shown by their p-values < 0; however, FC has an insignificant relationship with BI with a p-value > 0. The path coefficients for all the relationships are significant, indicating the strength of the relationships between the factors and behavioural intention. The highest path coefficient is for performance expectancy (0.201), followed by task value (0.182) and effort expectancy (0.133). The null hypothesis that states "no significant factors influence behavioural intention" is rejected based on the results. Instead, the alternate hypothesis states that PE, HM, SI, TV, FC and H significantly influence behavioural intention. These results imply that these factors determine students' willingness and attitude toward blended MOOCs.

Figure 8-1 shows that the seven factors mentioned in this study cause 53.7% of students' behavioural intention, with the remaining caused by other factors not mentioned in this study. This amount of the students' behavioural intentions was caused by changes in their perceived performance expectancy, task value, effort expectancy and others within the context of blended MOOC. Specifically, 8.8% of the changes were caused by the students' hedonic motivation, their performance expectancy caused by 20.1%, and their effort expectancy caused by 13.3%. In the same way, their social influence and perceived value of MOOCs caused 12.3% and 18.2% of the changes, respectively. It suffices to conclude that the students' social influence effort expectancy, task value and performance expectancy (listed in increasing order) caused more of the changes in their behavioural intentions. Their habit, hedonic motivation and facilitating conditions caused the least change in their behavioural intentions. The cumulative effect of these top three factors defined the 51.6% change in students' behavioural towards MOOCs and accounted for 36.8% of the student's actual use of MOOCs.

8.4.2 Factors affecting actual use of technology

Venkatesh et al. (2003) and Venkatesh et al. (2012), again, listed several factors that serve as antecedents to the actual use of technology, like blended MOOCs. These factors form the basis of the researcher's hypotheses in this section. The hypothesis under consideration is:

> *H2: Students' intention (BI), habit (H) and facilitating conditions (FC) will significantly influence their actual use (AU) of the blended MOOC system.*

Hypotheses H2a, H2b and H2c support this claim.

8.4.2.1 Behavioural Intention and actual use

> *H2a: Intention (BI) will have a positive influence on the actual use (AU) of the blended MOOC system.*

This hypothesis is critical because it answers how well students' goals match how they use the system. H2a has important implications for schools and companies that offer online courses. Studies have shown that the desire to use educational technology, such as blended MOOCs, is a strong predictor of the actual use of that technology. (Venkatesh et al., 2003; Venkatesh et al., 2012). Again, a study of 174 papers by UTAUT showed that the relationship between BI and AU was significant in 50 of 61 cases, giving it a predictive weight of 0.82. (Williams, Rana & Dwivedi, 2015). Therefore, H2a is an integral hypothesis to test if this study wants to learn more about the things that affect how engaged and successful students are in blended MOOC environments.

The statistics for the relationship between BI and AU are $\beta=0.386$, $t = 15.127 > 1.96$ *for* $\alpha = 0.05$, $p=0.000$, $f^2 = 0.17$, *CI (0.337, 0.437)*. The p-value shows that the null hypothesis is rejected, as there is sufficient evidence that BI affects AU. The path coefficient of 0.386 and p-value of 0.00 indicate that the relationship between BI and AU is significant and positive. This result agrees with earlier studies that showed how vital behaviour intention determines how people use technology. The finding means that the more students want to use technology, the more likely they are to use it. This finding signifies that students are more likely to use technology the more they plan to use it. Moreover, the path coefficient of 0.182 means that for every one-unit increase in AU, there is a corresponding 0. 386 unit rise in BI. The F-square value of 0.17 is a moderate effect size (Cohen, 1988, as cited in Hair et al., 2017), indicating that the independent variable (BI) accounts for 17.0% of the dependent variable (AU) variance. The confidence interval for the population mean between BI and AU is between 0.337 and 0.437 at a 95% confidence level. This CI indicates that the study would expect the true population mean between BI and AU to fall between 0.337 and 0.437 in 95% of the samples.

8.4.2.2 Habit and actual use

H2b: Habit(H) will have a positive influence on the actual use (AU) of the blended MOOC system.

Previous studies have shown that habits are a big part of how people use technology, which is likely to positively affect how people use blended MOOCs. For example, Venkatesh et al. (2012) found that habit greatly affected how long people use technology at work. Since habits are an excellent way to predict how people will use technology, they may be critical in blended MOOCs. This hypothesis is important because it shows that a student's authentic use of a system can be predicted by more than just whether they plan to use it.

The statistics for the relationship between H and AU are $\beta=0.146$, $t = 5.679 > 1.96$ *for* $\alpha = 0.05$, $p=0.000$, *CI (0.095, 0.195) and* $f^2 = 0.021$. The p-value indicates that the null hypothesis should be rejected, implying that H affects AU. This finding backs up what other studies have shown about the link between habits. The t-statistic for the relationship is 5.679, which shows a positive and significant link between Actual Use and Habit. This link has a p-value of 0.000, which means the results are statistically significant and not by chance. The relationship's path coefficient is 0.146, implying that for every one-unit increase in AU, there is a corresponding 0.146 unit rise in H. This finding shows that participants are more likely to use technology as they get used to it. The confidence interval (0.095, 0.195) indicates 95% confidence that the true population mean for the relationship between H and AU falls within this range. Since the confidence interval does not include zero, it further supports the idea that H and AU have a statistically significant relationship. The F-square value is 0.021, indicating a small effect of H on AU (Cohen, 1988, as cited in Hair et al., 2017). It tells us that 2.1% of the variation in AU can be explained by H.

8.4.2.3 Facilitating conditions and actual use

> *H2c: Facilitating conditions (FC) will have a positive influence on the actual use (AU) of the blended MOOC system.*

This hypothesis is critical because it shows that students' use of the blended MOOC system may depend on how many resources and help, they can access. Students' plans to use the system are greatly influenced by the availability of technical support and tools that encourage the adoption and use of technology in education. (Venkatesh et al., 2003; Venkatesh et al., 2012). Again, a study of 174 papers by UTAUT showed that the relationship between FC and AU was significant in 36 of 54 cases, giving it a predictive weight of 0.67. (Williams et al., 2015). These support systems are essential to FC's goal of getting schools to use technology. H2c is vital if researchers want to know how students use the blended MOOC system. Providing learners with the right tools and help can significantly affect how engaged they are and how well they do in MOOCs, showing how vital the facilitating conditions factor is in the suggested hypothesis.

The statistics for the relationship between FC and AU are $\beta=0.273$, $t = 10.065 > 1.96$ *for* $\alpha = 0.05$, $p=0.000$, $f^2 = 0.075$, *CI (0.219, 0.326)*. The p-value indicates that the null hypothesis should be rejected, implying that FC affects AU. This result indicates a good chance that the link seen is not just a coincidence. The path coefficient between FC and AU was 0.273, which shows that the two variables are moderate and positively related. The implication is that when FC goes up, AU also goes up. Again, 0.273-unit change in FC is associated with a unit change in AU. When students have easy access to technology and the tools and help, they need to use it well, they are likelier to be engaged, satisfied and do well in school. The f^2 of the relationship between FC and AU is 0.075, indicating a small effect size. This f^2 value means that FC can explain 7.5% of the variance in AU. The 95% confidence interval for the relationship between FC and AU ranges from 0.219 to 0.326. This CI means the study can be 95% confident that the true population parameter lies within this range. Also, since the CI does not include 0, it again shows that the relationship is statistically significant at 0.05.

At this juncture, it is important to return to the objective of this section, H2. The study's results support H2 because all three factors (Behavioural Intention, Facilitating Conditions, and Habit) showed a significant positive relationship with Actual Use of MOOCs. This result aligns with another study, showing how vital behavioural intention, enabling conditions and habits are for understanding how people accept and use technology (Lian & Yen, 2014; Venkatesh et al., 2012). The results showed that all of the sub-hypotheses for H2 were true. The link between Behavioural Intention (BI) and Actual Use (AU) was significant (t=15.127, p=0.000), and the path coefficient (β) was 0.386. This finding backs up other studies that show that behavioural intention strongly predicts technology use. This finding shows how vital behavioural intention is for predicting technology use (Venkatesh et al., 2012; Hsu & Lin, 2015). The link between Facilitating Conditions (FC) and Actual Use (AU) was also significant (T=10.065, p=0.000), with a path coefficient of 0.273. This result aligns with research, showing the importance of "facilitating conditions" in getting people to use new technologies. It shows that students' access to resources and help can make using MOOCs easier (Venkatesh et al., 2012). Lastly, the link between Habit (H) and Actual Use (AU) was significant (t=5.679, p=0.000), with a path coefficient of 0.146). This finding fits with another study, which states that habits can significantly impact how people use technology (Venkatesh et al., 2012; Hsu & Lin, 2015). It shows that students who use blended MOOCs are often more likely to keep doing so. This result agrees with other studies showing how important habits are in using technology. Overall, the results show that to get more people to use MOOCs; instructional designers should essentially work on changing how students plan to act, giving them the right resources and support, and helping them form good habits.

From Figure 9-1, students' actual use of blended MOOCs is directly influenced by their behavioural intentions, moderated by the facilitating conditions and habits defined in the UTAUT model. Currently, students' actual use of MOOC is 48.5%, and their behavioural intentions account for 36.8%. It means that 11.7% of students' actual use of MOOCs was by the moderating role of their habits and facilitating conditions. For instance, from the model, students' habits had an augmenting effect on the relationship between their behavioural intentions (11.9%) and their actual use of MOOC (14.6%). The result shows that though the students' habits contributed more to strengthening the relationship between their behavioural intentions and actual use of the MOOC, it had a more significant impact on their actual use of MOOC than their behavioural intentions. In a similar way, the facilitating conditions contributed to the 11.9% since it improved the impact of the students' behaviour on their actual use of MOOCs. As shown in the model, it had a 27.3% effect on the actual use of MOOCs compared to a 3.8% effect on students' behavioural intentions.

In summary, students' actual use of MOOCs was directly influenced by their behavioural intentions towards MOOCs, resulting from their performance expectancy, task value and effort expectancy. In addition, the impact of their behavioural intentions on their actual use of MOOCs was strengthened by their habits and the facilitating conditions.

8.5 Evaluating the presences of CoI and Students' Engagement

The Community of Inquiry (CoI) model by Garrison et al. (2000) and later extension from Shea and Bidjerano (2010) emphasises the importance of teaching presence, social presence, cognitive presence and learning presence to a) promote meaningful learning engagement in online environments and b) understand and design effective online learning environments, including blended MOOCs. Engagement has many dimensions. Since the study deals with blended MOOCs, the item indicators for engagement were adapted from the blended MOOC engagement model (Almutairi & White, 2018). In this part, the researcher discusses how four aspects of CoI are linked to student engagement. The hypothesis under consideration is:

H3: The four presences (Teaching, cognitive, social, and learning presence) of the CoI will significantly influence Student Engagement (SE) in blended MOOC.

Hypotheses H3a, H3b, H3c, and H3d support this claim.

8.5.1 Teaching Presence and Students' Engagement

H3a: Teaching presence (TP) will positively impact students' engagement (SE) in the blended MOOC system.

H3a is essential because it helps us to determine how teaching presence changes students' engagement in blended MOOCs. Several studies have found that teaching presence predicts students' engagement positively in online learning settings. (Arbaugh & Benbunan-Finch, 2006; Garrison, Anderson & Archer, 1999; Shea, Li & Pickett, 2006). For example, Arbaugh and Benbunan-Finch (2006) found that students' perceptions of learning and satisfaction in online classes were better when teaching presence was present. In the same way, Shea et al. (2006) found that teaching presence significantly affected how students thought they were learning and how engaged they were in online classes. Therefore, H3a is a vital hypothesis to examine because it can help us figure out how teaching presence affects how engaged students are in blended MOOCs and can help us to build suitable online learning environments. This idea is important because it talks about the role of the teacher's presence in getting students to participate in the blended MOOC system. Examining how it affects students ' engagement in blended MOOCs is essential because teacher presence is essential for getting students to learn and be engaged. Teaching presence is essential in online learning settings because it can improve students' engagement and learning. Higher levels of teaching presence are linked to higher levels of student satisfaction, the feeling that they are learning, and the feeling that the teacher is doing a good job. (Arbaugh and Benbunan-Finch, 2006). In the same way, a 1999 study by Garrison et al. found that teaching presence was a crucial factor in creating a sense of community among students in online learning environments. This environment, in turn, can improve students' engagement and learning results.

The statistics for the relationship between TP and SE are *β=0.109, t = 5.574> 1.96 for α =0.05, p=0. 000, CI (0.072, 0.149), f^2= 0.015*. The result indicates that the null hypothesis is rejected as TP affects SE, as the p-value attests. The t-statistics value was 5.574, meaning the association is statistically significant at the 0.05 significance level. The path coefficient for this relationship was 0.109, which shows that TP and SE are positively and significantly linked. The finding aligns with the previous research stated above. Based on the results, a higher quantity of teaching presence can make students more interested in blended MOOCs. This assertion backs up what other studies have found: that a teacher's presence is a key factor in keeping students interested and helping them do well in online learning environments. (Shea et al., 2010; Garrison et al., 2010). The path coefficient of 0.109 shows that TP increases by 0.109 units for every one-unit increase in SE. This finding shows that teaching presence strongly predicts how much students will participate in blended MOOCs. The confidence interval for this relationship at the 95% level ranges from 0.072 to 0.149. This CI tells us that the study is 95% confident that the true population mean of TP on SE lies between these two values. Since the confidence interval does not include zero, thus, it can be concluded that TP has a significant positive effect on SE. The F-square is 0.015, a negligible effect size (Cohen, 1988, as cited in Hair et al., 2017), indicating that TP explains 1.5% of the variance in SE.

8.5.2 Cognitive Presence and Students' Engagement

H3b: The students' cognitive presence (CP) will positively impact their engagement (SE) in the blended MOOC system.

A number of studies have shown that cognitive presence is vital for online learning and that it has an effect on how engaged students are. For example, Garrison and Akyol (2013) found that cognitive presence positively predicted students' engagement in online learning settings. This study shows that cognitive presence is an essential factor affecting students' engagement in blended MOOCs. Also, Garrison et. (2003) say that cognitive presence is vital to making online and blended learning settings meaningful. They said that cognitive presence is essential for getting students interested, helping them to learn deeply, and making new information. Lee (2014) found that students were much more engaged in online talks when their cognitive presence was high. Thus, if H3b is true, it would be more proof that cognitive presence is vital for getting students more involved in mixed MOOCs. Shea et al. (2009) did a study and found that cognitive presence was a positive predictor of student satisfaction and how much they thought they were learning. It also had a positive effect on learning outcomes in online classes.

The statistics for the relationship between CP and SE *are* $\beta=0.194$, $t = 7.140 > 1.96$ *for* $\alpha =0.05$, $p=0.000$, $f^2=0.036$, *CI (0.141,0.247*). This result indicates that the null hypothesis is rejected as CP affects SE, as the p-value attests. This relationship has a t-statistic of 7.140 and a p-value of 0.000, indicating that the results are statistically significant. The path coefficient for this connection was 0.194, showing a CP and SE linkage, indicating that for every unit increase in SE, there is a corresponding 0.194 increase in CP. The present study's results show that CP significantly affects students' engagement in blended MOOCs. The result aligns with other studies, showing how robust instructional design and cognitive engagement are for keeping students interested and improving their learning in online and blended settings. (e.g., Wang & Newlin, 2002; Kirschner & Karpinski, 2010). The finding means that student engagement increases as cognitive presence increases. This study found that when students can construct and confirm meaning through sustained reflection and discourse (cognitive presence), they are more likely to be engaged in their learning (student engagement). The F-square value for the relationship between CP and SE is 0.036, which is a small effect (Cohen, 1988, as cited in Hair et al., 2017). It also indicates that the predictor variable (CP) explains 3.6% of the dependent variable (SE) variance. The confidence interval (2.5% and 97.5%) for the relationship between CP and SE is 0.141 and 0.247, respectively. Thus, the study can be 95% confident that the true population parameter of the relationship between CP and SE falls between 0.141 and 0.247.

8.5.3 Social Presence and Students' Engagement

H3c: The students' social presence (SP) will positively influence their engagement (SE) in the blended MOOC system

Many studies have been conducted on social presence in online learning settings, finding a link between social presence and student engagement (Ma et al., 2022). It is vital to test Hypothesis H3c because social presence is a key part of online learning environments that help students to connect, communicate, and work together. Several studies have shown that students are more engaged in online learning settings when they have a social presence. For example, Richardson et al. (2017) found that social presence positively predicted how much students thought they were learning and how satisfied they were with their online classes. In another study, Rovai and Jordan (2004) found that social presence was linked to how much students thought they were learning and felt like they were part of a group. Also, a study by Bergdahl et al. (2020) found that social presence is a variable of engagement that a) predicts better academic success, b) is suitable for student engagement and c) outcomes in online settings. Overall, empirical studies show that social presence is a key factor in keeping students engaged and satisfied in online learning environments; thus, testing its effects in blended MOOCs is essential. Teachers and course designers can learn how to get students more involved in these classes by finding a link between social presence and student engagement in blended MOOCs.

The statistics for the relationship between SP and SE are $\beta=0.082$, $t = 3.595 > 1.96$ *for* $\alpha=0.05$, $p=0.000$, *CI (0.039, 0.128)*, $f^2=0.007$). This result indicates that the null hypothesis is rejected as CP affects SE, as attested by the p-value. The t-statistic and p-value shows that the SP and SE link is statistically significant at 0.05. The path coefficient of 0.082 shows that TP increases by 0.082 units for every one-unit increase in SE. The indication is that the more social presence students feel in blended MOOCs, the more likely they are to be involved. This study's results align with other studies, showing how significant social presence increases engagement in online and blended learning settings. For example, Rovai and Barnum's study from 2003 found that students were more likely to be engaged in online studies when they had a strong social presence. The confidence intervals (0.039, 0.128) provide a range of values within which the true value of the population mean of the relationship between SP and SE is expected to lie with a 95% level of confidence. In other words, if the sample were repeated severally, the population mean is expected to fall within this range in 95% of the samples. In this case, the confidence interval does not include zero, which indicates that the relationship between

SP and SE is statistically significant. The F-square of 0.007 has a negligible effect size (Cohen, 1988, as cited in Hair et al., 2017), suggesting that SP explains 0.7% of the variation in SE.

8.5.4 Learning Presence and Students' Engagement

H3d: The students' learning presence (LP) will positively impact their engagement (SE) in the blended MOOC system.

Students are more likely to be interested in the blended MOOC system if they are directly involved in the learning process, which is what H3d claims. This statement clearly supports the idea that student engagement is an important predictor of academic success in online and blended learning settings. Learning presence is more apparent when students are actively asked to work together through educational design. Learning presence includes self-efficacy and other cognitive, behavioural and emotional characteristics that help online learners to self-regulate. Several studies have shown that learning presence and student engagement in online and blended learning environments are related in a good way (Angelaina & Jimoyiannis, 2012; Popescu & Badea, 2020; Richardson & Swan, 2003; Wicks et al., 2015). For instance, Popescu and Badea (2020) found that learning presence strongly predicted students' behaviour in online classes. Angelaina and Jimoyiannis (2012) noticed that students learn more when participating in educational writing activities. They also found that students participated in educational blogging activities in different ways and that their learning presence changed over time. Wicks et al. (2015) also found a link between the learning presence and the number of connections between students in a network. Thus, students with more learning presence are more likely to participate in online discussions and think critically. The results show that the H3d is essential. They suggest that promoting learning presence may be essential to getting more students involved in blended MOOCs. Lastly, Roussinos and Jimoyiannis (2013) found that how students work together and interact during wiki tasks affects their learning. Again, they found that the strong connections between students led to more conversations, higher levels of learning presence, and the joint creation of meaning in the wiki group. Hypothesis H3d is essential because it asserts that the design of the course, the teaching methods, and the learning activities should help the students build their learning presence so that they are more interested and involved in the course. Therefore, suppose the hypothesis is supported by real-world evidence in that case, it can help teachers and instructional designers create and run effective blended MOOC courses that help students develop their learning presence and, as a result, improve their engagement, satisfaction, and academic performance.

The statistics for the relationship between LP and SE are *β=0.350, t = 13.04> 1.96 for α =0.05, p=0.000, f^2= 0.136, CI(0.299, 0.403).* This result indicates that the null hypothesis is rejected as CP affects SE, as the p-value attests. The p-value and the t-statistic demonstrate that the connection between LP and SE is not a coincidence but statistically significant. The finding agrees with prior studies mentioned above: a student's learning presence is crucial to their engagement in an online learning environment. The result shows that students are more likely to be interested in a blended MOOC when they think there is much learning, can use the tools of blended MOOCs and regulate themselves for learning. The path coefficient of 0.350 shows that LP increases by 0.350 units for every one-unit increase in SE. The F-square of 0.136 has a small effect size (Cohen, 1988, as cited in Hair et al., 2017), suggesting that LP explains 13.6% of the variation in SE. This value can be interpreted as the effect size. The confidence intervals (2.5%) and (97.5%) are 0.299 and 0.403, respectively. This CI denotes that the study can be 95% confident that the true population mean of the LP and SE relationship falls within this range. Therefore, LP has a significant positive effect on SE, with a confidence interval ranging from 0.299 to 0.403.

Now, the study come back to H3 itself; the t statistics are higher than the critical T value of 1.96 for a significance level of 0.05. The result is that the relationships are significant at the 0.05 level. All of the p-values are less than 0.05, meaning the results are statistically significant and are not likely to have happened by chance. The path coefficients for the relationships range from 0.082 to 0.350, which shows a moderate positive relationship between the presence of the CoI and student engagement in blended MOOCs. Previous studies have shown that the CoI framework is essential for increasing engagement in online and blended learning environments, which these results support (Garrison et al., 2010; Garrison and Cleveland-Innes, 2005; Shea et al., 2010; Veletsianos

& Kimmons, 2012). The CoI framework stresses the importance of creating a supportive, interactive learning community where students feel involved and driven to participate (Garrison et al., 2010). The results show that the four presences can make students more interested in blended MOOCs.

The R square score for H3 is 0.568, which shows a moderately positive link between the four presences of CoI and students' engagement in blended MOOCs. This result shows that when the four presences of CoI are present, students are more likely to be interested in the course. The result for H3's R^2 which is 0.568, indicates that the four presences of CoI explain 56.8% of the difference in how engaged students are in blended MOOCs. This result means that the four presences of CoI are essential factors that affect how engaged students are in blended MOOCs. The path coefficient of SP (0.082) suggests a weaker relationship than the other three presences, while the highest path coefficient is for LP (0.350), which suggests a strong relationship. The result indicates that LP is the most influential presence among the four in promoting blended MOOCs. The high path coefficient for LP shows that having a supportive environment that makes it easy for learners to self-regulate their learning is critical if researchers want to get students involved in blended MOOCs. On the other hand, CP and TP can be grown by helping learners with their training and teaching.

Overall, the results show that teachers and instructional designers should create an environment that helps students learn independently, encourages interaction, and gives clear instructions and pedagogical support. These practices can help students to get more involved, making them more satisfied and helping them do better in blended MOOCs.

8.6 To explore how students' engagement influences their satisfaction and perceived academic performance

The end goal of IS/IT solution in general and EdTech is explicitly its use to enhance learning to produce better learning outcomes. This objective wants to determine whether students' engagement in blended MOOCs can lead to their satisfaction and academic performance. Thus, the hypothesis to test is:

H4: With the blended MOOC environment, the effect of student engagement (SE) on student satisfaction (SS) is significant, and the effect of SE on perceived academic performance (AP) is significant.

Alternatively, H4 can also be split into two separate null hypotheses:

H4a: The effect of student engagement (SE) on student satisfaction (SS) is significant within the blended MOOC system.
H4b: The effect of student engagement (SE) on perceived academic performance (AP) is significant within the blended MOOC system.

8.6.1 Students' engagement influences their satisfaction

H4a: The effect of student engagement (SE) on student satisfaction (SS) is significant within the blended MOOC system.

A study by Kuo et al. (2014) found that student engagement positively affects student satisfaction in online courses, which suggests that H4a is a reasonable hypothesis to test in the context of blended MOOCs. Again, Kuo et al. (2014), it was determined that students held the perception that interaction played a crucial role in their learning experiences. Additionally, the study found that students expressed a moderate level of satisfaction with their blended learning course. Additionally, it was discovered that the interaction between learners and content exhibited the highest correlation with student satisfaction. Additionally, recent findings have demonstrated that interpersonal interactions enhanced student satisfaction and perceived progress in an online course. In addition, the study conducted by Ayanbode et al. (2022) found that satisfaction played a significant mediating role in the association between interactions and perceived progress. According to Baber (2020), various factors, including classroom interaction, were found to have a significant influence on students' satisfaction. According to the study conducted by Joo et al. (2011), it was determined that interaction emerged as one of the significant predictors of students' satisfaction. The papers stated above support the importance of investigating this relationship in the context of blended MOOCs.

These statements suggest that H4a is a reasonable hypothesis to test in the case of blended MOOCs. Also, Ayanbode et al. (2002) found that students' interactions in an online class positively affected their satisfaction and their sense that they were making progress, and that satisfaction played a vital role in the relationship between interactions and academic performance. Baber (2020) also found that contact in the classroom, among other things, greatly affected how satisfied students were. Joo et al. (2011) found that connection was among the most critical factors in predicting student satisfaction. The articles listed above show how important it is to study the relationship between engagement influences satisfaction in the context of blended MOOCs.

The statistics for the relationship between SE and SS are *β=0.643, t = 35.437, and p=0.000, CI (0.606, 0.678), f^2= 0.704.* These statistics ($p<0.05$ and $t>1.96$ for $\alpha=0.05$) show that the null hypothesis should be rejected since engagement influences student satisfaction. Once more, the path coefficient for SE is determined to be 0.643, signifying a robust positive association between student engagement and student satisfaction in blended MOOCs. This discovery is consistent with previous scholarly investigations (Artino & Stephens, 2009) that established a correlation between student engagement and student satisfaction. Furthermore, the β coefficient suggests a positive relationship between students' satisfaction and engagement, with a 0.643 unit increase in engagement for every unit increase in satisfaction. The confidence interval for the relationship between SE and SS ranges from 0.606 to 0.678, which indicating the study can be 95% confident that the true population parameter (mean) for these two variables falls within this range. The f-square value is 0.704, showing a huge effect of SE on SS. The indication is that SE explains 70.4% of the variance of SS. From Figure 9-1, the R square of 0.413 means that approximately 41.3% of the variation in students' satisfaction (dependent variable) can be explained by their engagement (independent variable) in blended MOOCs. Overall, H4a is significant because it demonstrates the importance of student participation in blended MOOC contexts and suggests that increasing student engagement can boost course completion rates and overall satisfaction. Educators and instructional designers need to understand what elements influence students' performance in blended MOOCs to provide engaging and motivating lessons for their students. Having students interested in what they are learning is crucial because it increases their chances of performing well academically and persisting in their studies. Educational institutions and teachers must also increase student satisfaction and performance in MOOCs and blended MOOCs to keep their reputation and attract new students.

8.6.2 Students' engagement influences their academic performance

H4b: The effect of student engagement (SE) on perceived academic performance (AP) is significant within the blended MOOC system.

Lei et al. (2018) conducted a meta-analysis comprising 69 independent studies with a total of 196,473 participants. The findings of this study revealed two key results. Firstly, a moderately strong and positive correlation was observed between overall student engagement and academic performance. Secondly, an examination of the specific domains of behavioural, emotional, and cognitive engagement indicated that nearly all of these domains exhibited a positive correlation with students' academic performance. The statistics for the relationship between SE and AP are $\beta=0.588$, $t = 30.751 > 1.96$ *for* $\alpha = 0.05$, $p=0.000$, $f^2=0.529$, *CI (0.551, 0.625)*. These statistics ($p<0.05$ and $t > 1.96$) show that the null hypothesis should be rejected since engagement influences academic performance. Again, SE has a path coefficient of 0.588, indicating a strong positive link between Student Engagement and perceived academic performance in blended MOOCs. Additionally, the β-value indicates that for each unit increase in academic performance, there is a 0.588 unit increase in their engagement. This finding aligns with earlier research (Breslow et al., 2013; Kahu, 2013) that found a link between student engagement and academic performance. An f-square of 0.529 for SE implies it considerably affects SE (Cohen, 1988, as cited in Hair et al., 2017). The result tells that SE explains 52.9% of the variance in AP. The 95% confidence interval for the relationship between SE and AP is (0.551, 0.625). This CI means the study can be 95% confident that the true population mean of the relationship between SE and AP falls within this interval. Since the confidence intervals do not include 0, it indicates that the relationship between SE and AP is statistically significant at the 0.05 level. Finally, from Figure 9-1, the R square of 0.346 means that approximately 34.6% of the variation in perceived academic performance (dependent variable) can be explained by their engagement (independent variable) in blended MOOCs. Overall, H4b is vital because it shows how critical engagement is in blended MOOC environments; it says engaging students can make them do well in their learning experience. The result shows that Student Engagement significantly predicts perceived academic performance in blended MOOCs. Educators and instructional designers need to know what factors affect how well students do in blended MOOCs so they can create compelling and exciting learning settings. By figuring out what makes students do well, teachers can make classes that help students learn more. Understanding the factors influencing students' performance in blended MOOCs is essential for educators and instructional designers to develop effective and engaging learning environments. Educators can design courses that better support students' learning outcomes by identifying the factors that positively impact students' performance.

8.7 How does the student's actual use of MOOCs influence their engagement in the MOOC system?

H5: The effect of the Students' Actual use (AU) of MOOCs does not significantly influence their Engagement (SE) in blended MOOCs.

A number of studies support the idea that the actual use of EdTech, such as blended MOOCs, will change students' engagement. For example, Arbaugh and Benbunan-Fich (2007) found that students were more engaged in online learning settings when they used technology. Similarly, Almutairi and White (2018) found that using technology in blended learning settings made students much more engaged. UTAUT is a common way to explain how and why people use new technologies, including educational technologies (Venkatesh et al., 2003). Venkatesh et al. (2003) again found that how people actually use technology is a key factor in how they plan to use it. They noted that real use is essential because it gives people hands-on experience with the technology, which can change how they think about how useful and easy it is to use. On the other hand, the CoI approach (Garrison et al., 2000) looks at what is needed for effective online learning. Engagement is key to the CoI model making learning group work (Kahu, 2013). Research has shown that engagement is a good predictor of how well students do in school. In this situation, it has been said that the actual use (AU) of educational technologies, as measured by UTAUT, can affect student engagement (SE) in online learning environments (Liaw et al., 2015; Orr et al., 2021). This statement fits with the idea that engagement is an essential predictor of learning outcomes in blended MOOCs and that technology use can help or hurt students' engagement with course materials and activities (Wang et al., 2015).

The t-statistics for the relationship between AU and SE is 10.106, with a p-value of 0.000, a path coefficient of 0.196, CI (0.158, 0.234) and f^2= 0. 065. The findings indicated that the t-measure exceeded the critical value of 1.96 at a significance level of 0.05. The p-value obtained was less than the predetermined significance level of 0.05, precisely 0.000. Consequently, the null hypothesis (H5) is rejected, indicating a statistically significant relationship between students' actual use (AU) and their engagement (SE) in blended MOOCs. Additionally, the β-value indicates that for each unit increase in SE, there is a 0.196 unit increase in AU. Furthermore, the F-square number was 0.065, which means that the size of the effect was small. The confidence intervals were (0.158, 0.234), which did not include zero, and the fact that the null hypothesis number of 0 is not in this range is another sign that the null hypothesis should be rejected. Again, the result shows a significant link between students' actual use (AU) and engagement (SE) in blended MOOCs. The R-square for SE was 0.568, meaning that Students' Actual use (AU) can explain 56.8% of the variation in their engagement (SE) in blended MOOCs. Based on the results, the study rejects the null hypothesis (H5) and conclude that there is a significant connection between students' actual use (AU) and their engagement (SE) in blended MOOCs. However, the f^2's effect size (0.065) was small, which means that Students' Engagement (SE) in blended MOOCs could also be affected by other things. It can be observed from Figure 9-1 that students' use of blended MOOCs directly influences their students' engagement. For instance, 56.8% of student engagement changes can be attributed to their actual use.

Ultimately, this study found that students' actual use significantly affects their engagement in blended MOOCs. Educators and instructional designers need to think about how students use blended MOOCs to get them to be more engaged and improve their learning experience. More studies are needed to determine what other things affect Students' Engagement (SE) in blended MOOCs. The literature on UTAUT, CoI, and student engagement in online learning environments supports the idea that blended MOOCs' real use (AU) will affect student engagement (SE). By looking into the connection between these concepts, teachers and instructional designers can learn how to create and use blended MOOCs that keep students interested and improve their learning. However, merely using technology does not mean students will be more interested. Other things, like how the blended MOOC is designed, the quality of the teaching materials, the learning setting, and the way the teacher teaches, can also significantly impact how engaged students are. It is essential to consider these things when looking into the link between actual use and engagement. The UTAUT suggests that other factors, such as perceived usefulness and ease of use, may mediate the relationship between actual use and engagement.

8.8 To explore how actual use and engagement influence students' satisfaction and perceived academic performance

This objective wants to determine whether using blended MOOCs for academic engagement can improve student satisfaction and academic performance. Thus, the hypothesis to test is:

H6: The effect of actual use (AU) and student engagement (SE) on student satisfaction (SS) is significant, and the effect of AU and SE on perceived academic performance (AP) is significant.

Alternatively, H6 can also split into two separate null hypotheses:

H6a: The effect of actual use (AU) and student engagement (SE) on student satisfaction (SS) is significant within the blended MOOC system.
H6b: The effect of actual use (AU) and student engagement (SE) on perceived academic performance (AP) is significant within the blended MOOC system.

Figure 9-1 shows these relationships: AU->SE, then SE-> AP, and AU->SE, then SE->SS. Thus, the study wanted to examine the combined effects of two independent variables (IVs), Actual Use (AU) and Student Engagement (SE), on the two dependent variables (DVs), Perceived Academic Performance (AP) and Student Satisfaction (SS), separately. As a way of achieving the said objective, multiple regression analysis was run with SPSS version 28 via "Linear Regression" with options such as "Statistics", "Descriptives", "Estimates", "Model fit", "Plots", "Histograms", "Normal probability plots", and "Diagnostic plots".

8.8.1 The combined effect of actual use and engagement on satisfaction

H6a: The combined effect of Actual use (AU) and Students' Engagement (SE) on Students' Satisfaction (SS) is significant.

The goal of this section was to use multiple regression analysis to find out what effect Actual use (AU) and Students' Engagement (SE) have on Students' Satisfaction (SS) as a whole. The multiple regression analysis result is shown in Table 8-2. The t-statistics value and the p-value indicate strong evidence against the null hypothesis, implying a significant relationship between AU, SE and SS. The R-squared value of 0.482 showed that AU and SE could explain 48.2% of the difference in SS. The beta coefficients for AU and SE were 0.193 and 0.567, respectively, implying that SE had a more significant positive effect on SS than AU. Both AU and SE were significant indicators of SS, as shown by the fact that their p-values were less than 0.001. With a p-value of less than 0.001, the constant value was also significant. The t-values for AU and SE were 11.908 and 35.018, respectively, which means that both predictor factors were essential in predicting SS. The constant's t-value was 11.153, which shows that the value of the constant was also significant. The ANOVA results showed that the model was a good fit for the data with an F-value of 1335.246 ($p < 0.001$), which is a significant number.

Table 8-2:Multiple Regression Analysis Results for the Effect of AU and SE on SS

Model	**Unstandardised Coefficients**		**Standardised Coefficients**	**t**	**Sig.**	**95.0% Confidence Interval for B**	
	B	**Std. Error**	**Beta**			**LB**	**UB**
(Constant)	.772	.069		11.153	<.001	.636	.908

AU	.145	.012	.193	11.908	<.001	.121	.169
SE	.686	.020	.567	35.018	<.001	.648	.725

Note: R=0.694, R Square = 0.482, Adjusted R Square = 0.481, F-value = 1335.246, Sig.(p-value) < 0.001, df=2872, N = 2875. Lower Bound (LB) and Upper Bound (UB).

Ultimately, this multiple regression analysis shows that AU and SE affect SS. Both AU and SE could be used to predict SS, but SE was a better indicator than AU. This result suggests that if students are more involved in blended MOOCs, they may be happier with the course as a whole. To determine whether the effect of AU and SE on SS performs better than that of SE alone on SS, this study compared the R-squared values of the two models to see if AU and SE on SS are better than SE on SS alone.

From Figure 9-1 and Table 9-2, the R-squared value for the combined effect of AU and SE on SS is 0.482, and that for the effect of SE alone on SS is 0.413. The R Square value of 0.482 for AU and SE on SS shows that they explain 48.2% of the variation in SS. This R2-value shows that AU and SE are important ways to predict SS. On the other hand, the R Square value of 0.413 for SE on SS shows that SE alone can explain 41.3% of the variation in SS. Based on these results, the effect of AU and SE together has a more significant link to SS than SE alone. This result is also supported by the standardised coefficients (Beta) for AU and SE in the multiple regression model. AU's beta value is 0.193, and SE's is 0.56. The beta value shows that SE has a more significant effect on SS, but adding AU makes the model better at predicting the future as a whole.

8.8.2 The combined effect of actual use and engagement on academic performance

H6b: The combined effect of Actual use (AU) and Students' Engagement (SE) on Academic Performance (AP) is significant.

Hypothesis H6b suggests that students' use and engagement within the blended MOOC system will positively influence their performance. This hypothesis is critical because it seeks to understand the relationship between students' engagement and use of the MOOC system and their academic performance.

Table 8-3:Multiple Regression Analysis of AU and SE on Academic Performance

Model	**Unstandardised Coefficients**		**Standardised Coefficients**	**t**	**Sig.**	**95.0% Confidence Interval for B**	
	B	Std. Error	Beta			LB	UB
(Constant)	.942	.078		12.088	<.001	.789	1.095
AU	.115	.014	.147	8.386	<.001	.088	.142
SE	.677	.022	.536	30.691	<.001	.634	.720

Notes R Square = 0.482, Adjusted R Square = 0.482, F-value = 1335.246, p-value < 0.001, df=2872, N = 2875. Lower Bound (LB) and Upper Bound (UB).

The t-statistics value and the p-value indicate strong evidence against the null hypothesis, implying a significant relationship between AU, SE and AP. The R-squared value of 0.482 (R^2 =0.482) showed that AU and SE could explain 48.2% of the difference in AP. The beta coefficients for AU and SE were 0.193 and 0.567, respectively, implying that SE had a more significant positive effect on AP than AU. Both AU and SE were significant indicators of AP, as shown by their p-values being less than 0.001. With a p-value of less than 0.001, the constant value was also significant. The t-values for AU and SE were 11.908 and 35.018, respectively, which means that both predictor factors were essential in predicting AP. The constant's t-value was 11.153, which shows that the value of the constant was also significant. The ANOVA results showed that the model was a good fit for the data with an F-value of 1335.246 ($F(2,2872) = 1335.246$, $p< 0.001$), which is a significant number.

8.9 Importance-Performance Map Analysis

The Importance-Performance Map Analysis (IPMA) is a valuable tool for decision-making because it provides a clear and concise representation of complex data and helps decision-makers to identify underperforming and overperforming factors. This result makes it easy to identify trade-offs between competing priorities. The IPMA is an excellent way to see how well different factors are being met and how important they are. It helps people to determine which things are most important to them and how well they are being cared for now. The IPMA that SmartPLS makes is a graph with two dimensions. The horizontal axis shows each factor's importance, and the vertical line shows how well each factor performs.

- "Importance" is how respondents or stakeholders value a construct or factor. It shows how important or significant each construct is thought to be. Higher scores from 0 to 1 indicate that respondents value the construct.
- Performance is how well each construct is doing compared to what respondents expected. It shows how well or effectively each construct works. Lower ratings indicate from 100 to 0 that the construct is not working as well as planned.

On the line, each factor is shown by a dot. The dot size shows how often the respondent talked about that factor. The factor's importance is shown by where the dot falls. To use the IPMA for decision-making, researchers split the constructs into four quadrants based on their importance and performance.

- The constructs in the upper-right quadrant are very important and perform highly to the respondents, meaning they work well and should be kept.
- The constructs in the lower-right quadrant are very important but have low success ratings, so they need improvement.
- The constructs in the upper-left quadrant are not very important but have a high-performance rate, which means they are doing too well, and resources could be moved elsewhere. They are an example of possible overdoing.
- The lower-left section has unimportant constructs that do not perform well, which means they can be moved around or thrown out.

When assigning priorities, the constructions that fall into the upper-right quadrant are seen as having a high priority, whilst the constructs that fall into the lower-left quadrant are regarded as having a low priority. Student satisfaction and perceived academic performance are the present study's two variables of interest. IPMA in Table 8-4 and Table 8-5 and their corresponding Figures 8.2 and 8.3 seeks to determine all the indirect and direct variables in the model that are important to the performance of students' satisfaction and academic performance. Tables 8-4 and 8-5 contain IPMA results based on a sample size of 2875 participants. The performance measure is based on how well the direct and indirect variables have contributed to satisfaction and academic performance, using the available resources within a given time frame.

Table 8-4: Performance and importance index values for Student Satisfaction for 2875 Participants

Constructs	Importance Index	Performance Index
PE	0.01	81.782
TP	0.07	81.728
CP	0.125	81.553
SE	0.643	81.161
LP	0.225	81.126
TV	0.009	80.984
HM	0.004	80.6
SI	0.006	80.541
BI	0.049	80.5
H	0.024	79.714
SP	0.053	79.684
EE	0.006	79.332
FC	0.036	78.792
AU	0.126	76.222

Table 8-4 and Figure 8-2 show the importance and performance indices for 14 different constructs that may affect Students' Satisfaction. The Importance Index runs from 0 to 1, with higher values showing that a construct is more important to student satisfaction. The Performance Index is also between 0 and 100, with higher numbers showing that a construct is doing a better job of satisfying students.

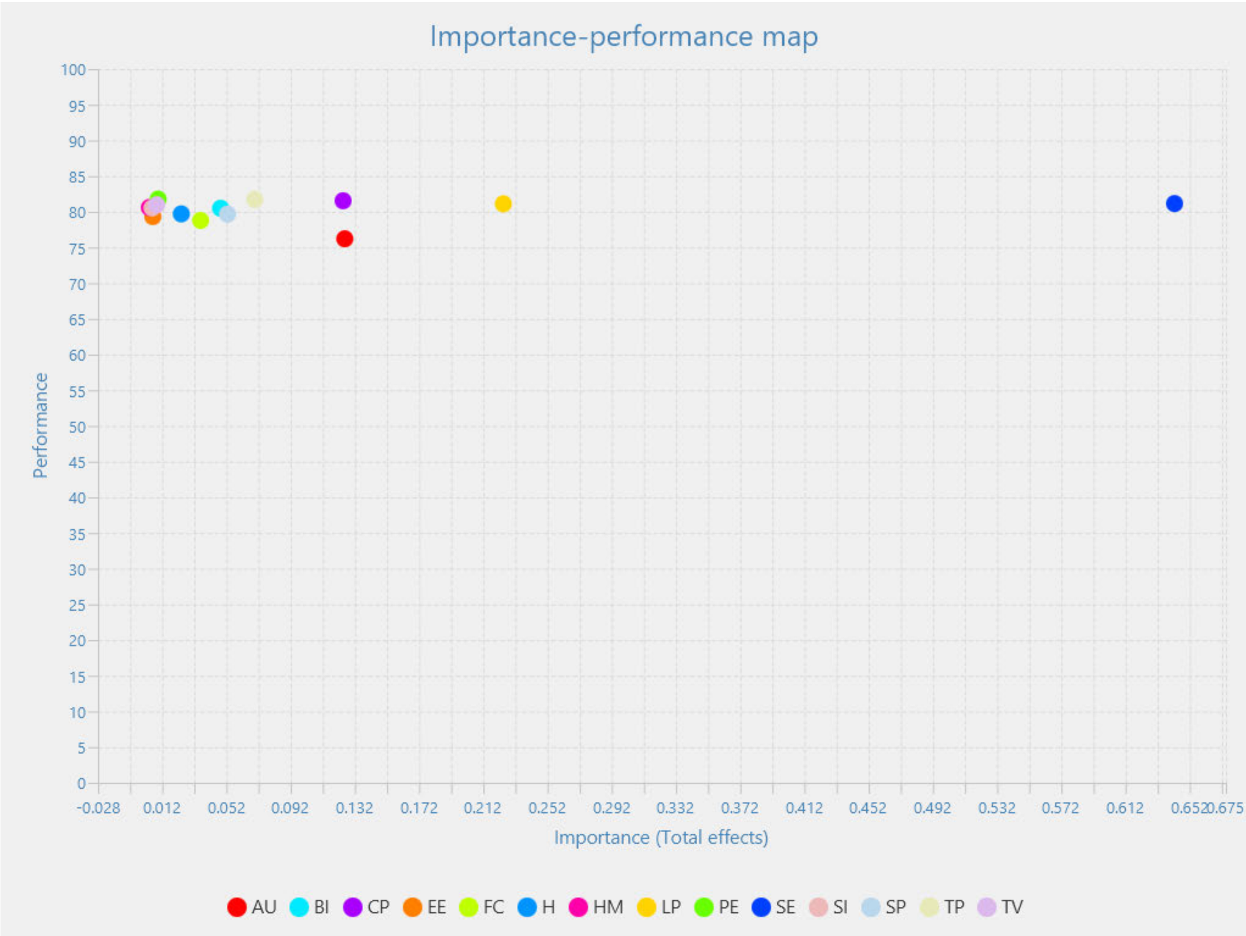

Figure 8-2. Importance-performance Map Analysis for Students' Satisfaction for 2875 Participants

Looking at the table, we can see that SE is the most important construct having an Importance Index of 0.643. This result shows that students value being interested in their classes and learning. On the other hand, SE has a Performance Index of 81.161 regarding how well it helps students to be satisfied. Even though this is still high, it is lower than others. With a score of 81.782, PE is the best-performing construct according to the Performance Index. CP, LP and AU are other constructs with high Importance Indices that may need more attention. However, their Performance Indices could be better than some other constructs, which suggests that these areas could need some work. Overall, the IPMA indicates that even though SE is the most important factor in student satisfaction, other factors may be doing a better job of making students satisfied. If educators and organisations want to improve student satisfaction, it is a good idea for them to work on improving the performance of factors other than SE.

Table 8-5: Performance and importance index values for perceived academic performance for 2875 participants

Constructs	Importance Index	Performance Index
AU	0.115	76.222
BI	0.045	80.5
CP	0.114	81.553
EE	0.006	79.332
FC	0.033	78.792
H	0.022	79.714
HM	0.004	80.6
LP	0.206	81.126
PE	0.009	81.782
SE	0.588	81.161
SI	0.005	80.541
SP	0.048	79.684
TP	0.064	81.728
TV	0.008	80.984

Regarding academic performance, the IPMA can help to find the areas that need improvement and figure out how to use resources to get the best results. The values displayed in the table show that SE has the highest Importance Index (0.588), which means that it is the most important construct. The Performance Index for LP is 81.126, which means it does the best out of all the mentioned constructs, even though it is not as important as SE. Based on this knowledge, it is possible to determine which of the constructs should be worked on the most. In this case, SE is the most important construct because it works just as well as LP, which has the best Performance Index. Thus, efforts should be put toward making SE work better. In this study, none of the constructs are in these two quadrants. Based on this study, educators would do well to focus on improving the performance of the SE and LP constructs since these are high-priority areas with high Importance Index values.

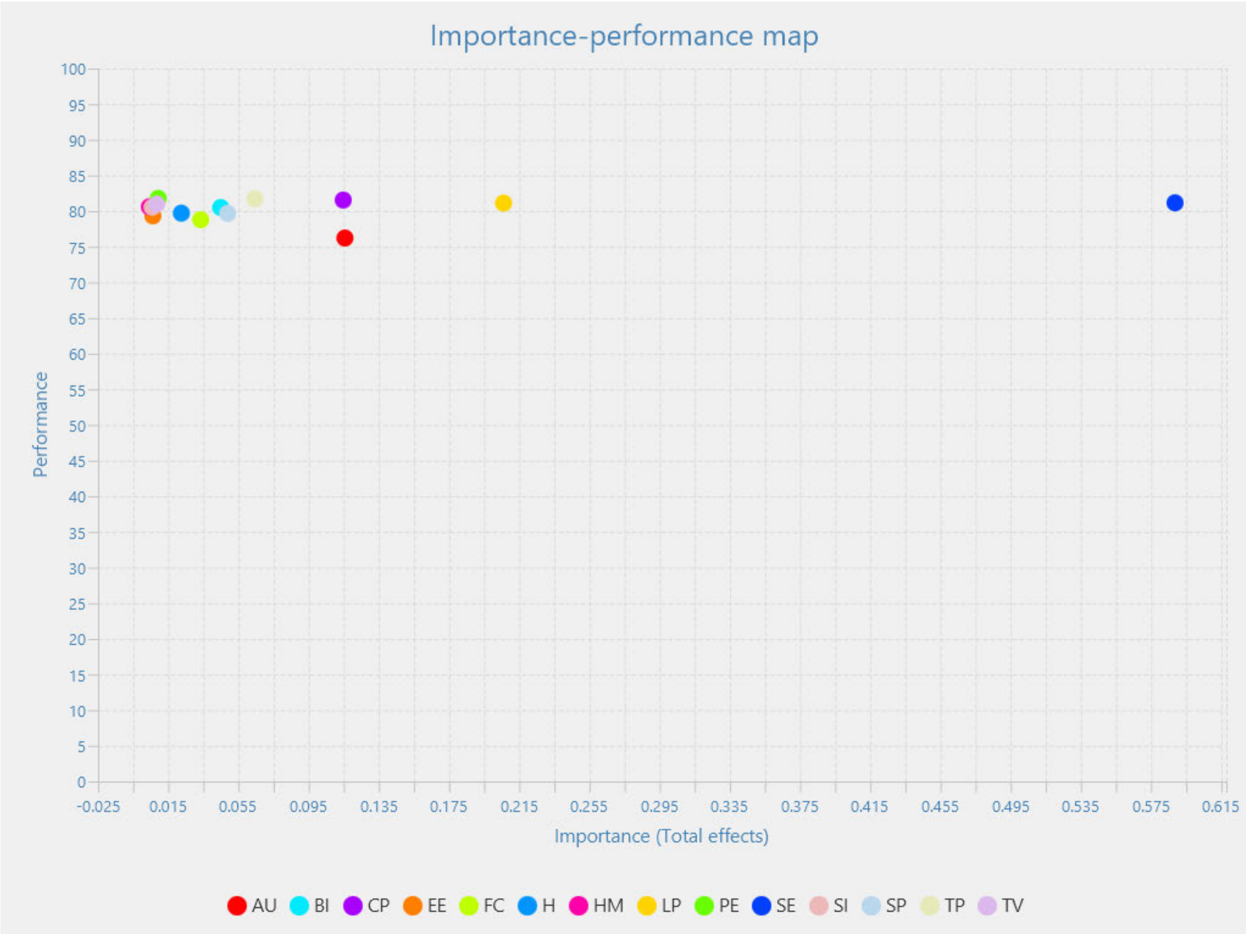

Figure 8-3. Importance-performance map Analysis for perceived academic performance for 2875 Participants

Comparing the IPMA for Students' Satisfaction and Academic Performance, the constructs with the highest Importance Index values differ in each case. The variables with the highest Importance Index values for Students' Satisfaction are SE (0.643), LP (0.225), and CP (0.125). When it comes to Academic Performance, CP (0.114), LP (0.206), and SE (0.588) have the best Importance Index values. Nevertheless, when it comes to Performance Index values, both constructs have similar values, running from

76.222 to 81.782 for Students' Satisfaction and from 76.222 to 81.782 for Academic Performance. This result means that both constructs need to improve what they do. Regarding policy, it may be necessary to focus on the ideas with the highest Importance Index values first since students think these are the most important. The implication is that researchers should focus on SE, LP and CP for Students' Satisfaction and for Academic Performance, they should focus on CP, LP and SE. But it is important to remember that all Performance Index numbers can be improved, so efforts should also be made to improve the performance of all constructs.

8.10 Summary

In all, eighteen hypotheses were tested in this study. From the objectives, the breakdown of the hypotheses is as follows: a) seven from assessing students' intention to use blended MOOCs in future; b) three from students' actual use of blended; c) determining students' relationship between the four CoI's presences and students' engagement had four hypotheses; d) evaluating students' engagement and its impact on students' satisfaction and the perceived academic performance had two; and e) two hypotheses from assessing students' actual use and engagement in blended MOOCs. The null hypotheses of all except one (FC->BI) were rejected. The implication is that blended MOOCs positively affect learning outcomes, which this study indicates as students' engagement, satisfaction and perceived academic performance. For the first objective, the top three factors for the UTAUT 2 model that greatly impacted behavioural intention were performance expectancy, task value and effort expectancy. Learning presence, which was not part of the original CoI model, outperformed the others, significantly impacting students' engagement. Chapter 9 will summarise the study's findings, conclusions, suggestions, and future research.

CHAPTER 9: FINDINGS, CONCLUSIONS AND RECOMMENDATIONS

9.1 Introduction

Section 9.1 restated the aim and objectives of the study and explored its essential findings and their broad ramifications. The study's main findings and their implications are discussed in Section 9.2. The chapter explores these findings' practical and theoretical ramifications in Section 9.3. This provides educators, institutions, and policymakers with helpful information and guidance on blended MOOCs. Section 9.4 provides detailed research-based recommendations. These stakeholder-specific strategies include educators, instructional designers, and policymakers. They aim to improve blended MOOC student engagement, satisfaction, and performance. The study's theoretical and practical value is illuminated in Section 9.5. This chapter explains how this research enhances current knowledge and shapes blended MOOC conversation. The chapter methodically examines the research's theoretical contributions in Section 9.5.1, challenging or expanding paradigms and notions. This expansion enhances blended MOOC theory.

In contrast, Section 9.5.2 shows how the study's findings can be applied in real life. This practicality helps educators, institutions, and students shape blended MOOCs. Section 9.6 provides a roadmap for scholars and researchers interested in mixed MOOCs to study them further. Explore these undiscovered locations for discoveries. Section 9.7 concludes this extensive voyage, summarising the study's findings. The key findings, consequences, and recommendations are integrated here. The conclusion of this research emphasises its importance in education.

The study's main aim was to evaluate how students' use and engagement in blended MOOCs will affect their satisfaction and perceived academic performance. The main research question was “how do students' usage acceptance and engagement with blended MOOCs influence their academic satisfaction and performance”? The following sub-objectives were pursued to achieve the key objective stated.

1) To investigate the determinants influencing learners' willingness to use blended MOOCs in the future. The key question was: How do UTAUT2 factors influence students' intention to use blended MOOCs?

2) To investigate the factors influencing learners' adoption and sustained use of blended MOOCs. The key question was: what factors influence students' actual use of technology in blended MOOCs?
3) To explore the impact of presences of the community of inquiry on students' engagement. The key question was: what presences of the community of inquiry impact students' engagement in blended MOOCs?
4) To explore the relationship between students' engagement and satisfaction in blended MOOCs. The key question was: how does students' engagement in blended MOOCs affect their satisfaction?
5) To explore the relationship between students' engagement and perceived academic performance in blended MOOCs. The key questions are: how does students' engagement in blended MOOCs affect their academic performance?
6) Examining how students' actual use of blended MOOCs influences their engagement. The key question was: to what extent does students' actual use of blended MOOCs influence their engagement?
7) To explore the impact of the combined effect of Actual use and students' engagement on their satisfaction in blended MOOCs. The key question was: how do students' actual use and engagement in blended MOOCs affect their satisfaction?
8) To explore the impact of the combined effect of Actual use and students' engagement on their perceived academic performance in blended MOOCs. The key question was: how do students' actual use and engagement in blended MOOCs affect their academic performance?

The study used the extended UTAUT model, the blended MOOC Engagement model and the revised COI model to create a model based on the argument that the actual use of MOOCs is what leads to engagement in it and subsequently impacts satisfaction and academic performance. The tenets of the three models formed the variables for the models of which the necessary nexus was established for actual use and engagement in blended MOOCs. A quantitative research method was used for the study design, sampling, and data collection processes. A structural equation modelling technique was used to design the model connecting the UTAUT and COI models and its subsequent link to students' satisfaction and academic performance. SmartPLS 4 software performed a partial least square regression analysis on the model. Details of the results were tabulated in figures and tables and discussed in line with the literature. A summary of the study's findings is compiled below.

9.2 The main findings of the Study and their implications

Several findings within this study's descriptive and inferential statistics are essential in considering how a student's use of and engagement in blended MOOCs may or may not impact their satisfaction and academic performance.

Firstly, the findings obtained from the descriptive statistics could be observed. Regarding the extended CoI, most students positively responded (over 85% agreed or strongly agreed) to each of the question items of constructs included in the model. Students generally had a positive perception and experience with the blended MOOC. They agreed or strongly agreed that they were engaged in the course, felt like they were learning, and experienced a sense of community. The exact amount of the level of agreement out of 2875 respondents for each construct is specified in the ensuing paragraphs.

- The results indicate that the teaching presence in the blended MOOC system was generally satisfactory, with a percentage of 94.6% of students expressing satisfaction. These students agreed or strongly agreed with the instruction quality provided within the blended MOOC framework. The students rated the teaching presence as being of high quality. The students perceived that their instructors displayed a genuine interest in the subject matter and fostered a sense of belonging among them.
- Again, 91.5% students felt connected to and socially involved with other students in the classroom. The results show that a large percentage of students, 87.6%, felt like they belonged to a social group in the blended MOOC setting.
- The study also found that students' cognitive presence was very high, with a rate of 95.1 % being recorded. The current finding shows that the students thought they were actively involved in building and reviewing ideas and making links between different ideas and the information they were taught in class. This endeavour constitutes a crucial component of cognitive presence as it

demonstrates the student's ability to apply acquired knowledge in significant contexts within and beyond the confines of the educational setting. Students favourably rated the cognitive presence. The individual experienced a sense of active engagement in constructing and exploring concepts while establishing links between disparate ideas.

- The majority of respondents (95.1%) indicated agreement with the notion of learning presence, as evidenced by their perception of actively engaging in the learning process within the blended MOOC system. This discovery is encouraging as it indicates that the students perceived themselves to be acquiring knowledge and enhancing their skills within the context of the course. The students rated the learning presence highly favourably. The students perceived a sense of progress and advancement in their academic pursuits throughout the course.

Regarding the blended MOOCs engagement model, the subsequent observations were noted.

- The results indicate that a significant majority of respondents (93.5%) agreed or strongly agreed about their level of MOOC engagement in the blended MOOC. The discovery mentioned above is a positive development as the active participation of students enhances academic performances and favourable outcomes in blended MOOCs.
- Most participants (96.2%) agreed or strongly agreed regarding their engagement level in campus-based courses. The aforementioned heightened level of engagement implies that courses conducted on campus may possess more significant levels of engagement in comparison to MOOC engagement.

In general, the outcomes of this investigation indicate that the blended MOOC mode was positively received by students and proved to be a fruitful learning encounter for them. Nonetheless, the potential for enhancement exists, such as augmenting the social presence within the course and enhancing the course's level of engagement. The participants were actively involved, perceived a sense of knowledge acquisition, and felt belonging. The following are supplementary reflections regarding the results. The commendable evaluations for every construct outlined above indicate that the blended MOOC was effectively planned and executed. The course fostered a conducive learning atmosphere facilitating student engagement and providing ample support. The positive evaluations regarding the quality of instruction and the level of social interaction imply that the educators successfully fostered connection and active participation among the students, cultivating a sense of belonging within the academic community. The course effectively promoted student learning, as evidenced by the high cognitive and learning presence ratings. The course facilitated the students' active construction and exploration of ideas, enabling them to connect various concepts and apply their acquired knowledge to practical, real-life scenarios.

The observations discussed in this paragraph deal with the factors affecting the extended UTAUT for Blended MOOC use. The question items for the constructs in this category had more than 49% agreement or strong agreement responses on each of the items of constructs.

- Performance expectancy: 93.5% of the participants agreed or strongly agreed with the efficacy of blended MOOCs in enhancing their academics. This factor suggests that students are likely to utilise blended MOOCs when they believe that such courses can enhance their academic performances. Once more, it is widely held among students that blended MOOCs will facilitate their knowledge acquisition and enhance their competencies.
- Effort expectancy: 90.1% of the respondents agreed or strongly agreed with the ease of utilising blended MOOCs. This factor suggests that the probability of students utilising blended MOOCs is higher when they perceive it to be less burdensome and not excessively demanding in terms of time and difficulty.
- Social influence: 93.1% of the participants agreed or strongly agreed regarding the perceived approval of their utilisation of blended MOOCs by their close associates and the university. This factor does not necessarily indicate a higher probability of students adopting blended MOOCs solely due to peer influence; they must also perceive it as beneficial and consider it mandatory, as in the case of UCC.
- Facilitating conditions: 90.4% of the participants agreed or strongly agreed regarding the availability of necessary resources and support for utilising blended MOOCs. The presence of requisite technology and resources does not necessarily indicate an inclination among students to engage with blended MOOCs; the perceived utility of such courses is a crucial determinant. The likelihood of

students utilising blended MOOCs positively correlates with their ability to obtain requisite technological resources and receive adequate support.

- Hedonic motivation: 88.7% of participants agreed or strongly agreed with their inclination to derive pleasure from utilising blended MOOCs. This variable indicates that the probability of students utilising blended MOOCs is higher when they perceive them to be enjoyable, rewarding, or efficacious.
- Habit: 87% of participants agreed or strongly agreed that they are familiar with or can automatically perform activities involving blended MOOCs. This figure is the lowest since most respondents, especially levels 100 and 800, were using blended MOOCs for the first time.
- Task value: 94.7 % of participants agreed or strongly agreed with the usefulness of incorporating blended MOOCs in their learning experience. The likelihood of students utilising blended MOOCs is positively correlated with their perception of the relevance and significance of activities performed concerning learning.
- Behavioural intention: 88.7% of the participants agreed or strongly agreed towards adopting blended MOOCs in their future learning endeavours. This variable indicates that the probability of students using blended MOOCs is higher if they intend to do so in the future.
- Actual use: 81.6% of the participants confirmed their utilisation of blended MOOCs in the past by agreeing or strongly agreeing with the statement. This factor indicates that students are utilising blended MOOCs to a notable degree.

These findings indicate the potential of blended MOOCs as an innovative educational technology. Students perceive blended MOOCs as effective learning tools that are user-friendly and socially influenced. Students' adoption of blended MOOCs is influenced by several factors, including access to technology and support, perceived enjoyment and rewards, prior positive experiences with MOOCs, perceived relevance and importance of the material, and intention to use them in the future. Blended MOOCs have garnered positive feedback from students or have been positively received by students and hold promise for enhancing student performance, engagement, and satisfaction.

Concerning the benefits of blended MOOCs, a significant proportion of participants, precisely 91.3% and 91.2%, agreed or strongly agreed with the constructs of students' satisfaction and perceived academic performance, respectively. The proposition posits that students' overall satisfaction and perceived academic performance about using blended MOOCs is predominantly affirmative. The substantial proportion of participants who expressed agreement or strong agreement with both variables suggests that the utilisation of blended MOOCs is efficacious in augmenting student satisfaction and perceive academic performance.

At this point, the objectives mentioned in Section 9.1 could be considered. The significance threshold is typically established through statistical tests and indicated by p-values, usually set at a significance level of 0.05 or 5% in social science research. Therefore, the relationships reported in this study have met this standard of significance, providing robust evidence of their validity. The implication is that the observed relationships are unlikely to have occurred by chance alone.

9.2.1 Finding relating to the determinants of behavioural intention for blended MOOCs

In the matter of factors affecting behavioural intention to use blended MOOCs, except for facilitating conditions, all the other six factors effort expectancy (EE), performance expectancy (PE), hedonic motivation (HM), social influence (SI), task value (TV) and habit(H), have positive relationships with behavioural intention (BI). The highest path coefficient is for performance expectancy (0.201), followed by task value (0.182) and effort expectancy (0.133). However, the seven factors mentioned in this study cause 53.7% of students' behavioural intention (See Figure 9-1 and Table 9-1).

9.2.2 Finding relating to the factors affecting the continued use of blended MOOCs

Behavioural intention is one of the key factors to actual use, with seven antecedent factors mentioned previously in Section 9.2.1. Regarding the determinants influencing learners' willingness to use blended MOOCs in the future, the study observed that behavioural intention, facilitating conditions, and habit significantly positively correlate with the actual use of MOOCs (see Figure 9-1 and Table 9-1). It was found that the coefficient of determination (R^2 or R-squared) value was 48.5%, indicating that BI, FC, and H collectively explain 48.5% of the variance in AU. The results show that all three factors significantly influence AU, with BI having the most substantial effect (β=0.386), followed by FC (β=0.273) and H (β=0.146). However, the remaining 51.5% of the variance in AU cannot be explained by the model, which suggests that other factors can influence students' actual use of MOOCs. Finally, the model's predictive power (54% for BI and 49% for AU see Figure 9-1) falls short of that known for UTAUT, which accounts for 74% of the variation in behaviour intention and 52% in technology adoption(Venkatesh et al., 2003).

9.2.3 Finding relating to the effect of students' engagement within blended MOOCs

Regarding exploring the impact of blended MOOCs on students' engagement, the results show that all four presences (teaching, cognitive, social, and learning presence) of the CoI framework significantly influence student engagement in blended MOOCs (See Figure 9-1 and Table 9-1). The most substantial impact on students' engagement is from learning presence(β=0.350), cognitive(β=0.194), teaching (β=0.109), and social presence(β=0.082) in that order. The R square score is 0.568, indicating that the four presences of CoI explain 56.8% of the difference in how engaged students are in blended MOOCs.

9.2.4 Finding relating to the relationship between students' engagement and satisfaction or perceived academic performance in blended MOOCs

From Figure 9-1 and Table 9-1, it is evident that the effect of students' engagement (SE) on their satisfaction (SS) is significant within the blended MOOC system, with a path coefficient of 0.643 (β=0.643). The R square of SS is 0.413, indicating that approximately 41.3% of the variation in students' satisfaction can be explained by their engagement in blended MOOCs. The effect of student engagement (SE) on perceived academic performance (AP) is significant within the blended MOOC system, with a path coefficient of 0.588. The R square of AP is 0.346, indicating that approximately 34.6% of the variation in perceived academic performance can be explained by their engagement in blended MOOCs. Students' engagement significantly positively impacts students' satisfaction and perceived academic performance within the blended MOOC system, with the effect being more significant for the former than the latter.

9.2.5 Finding relating to the relationship between the actual use of blended MOOCs influences their engagement

Relating to examining how students' actual use of blended MOOCs influences their engagement. Students' actual use (AU) of blended MOOCs significantly impacts their engagement (SE) with a path coefficient of 0.196. The R-squared value of 0.568 indicates that AU can explain 56.8% of the variation in SE.

9.2.6 Finding relating to the combined effect of Actual use and students' engagement on their satisfaction or perceived academic performance in using blended MOOCs

Pertaining to exploring the impact of the combined effect of Actual use and students' engagement on their satisfaction or perceived academic performance in blended MOOCs. Students' actual use (AU) and engagement (SE) are both significant predictors of student satisfaction (SS) in blended MOOCs. SE had a more significant positive effect on SS than AU, with beta coefficients of 0.567 and 0.193, respectively. The R-squared value of 0.482 indicates that AU and SE can explain approximately 48.2% of the variation in SS, which is better than that of SE alone, which explains 41.3% of the variation in SS. In like manner, students' actual use (AU) and engagement (SE) are both significant predictors of perceived academic performance (AP) in blended MOOCs. The R-squared value of 0.482 indicates that AU and SE can explain approximately 48.2% of the variation in AP. This R-squared value of 48.2% for AU and SE is better than that of SE alone on AP, which is 34.6%. The beta coefficients for AU and SE were 0.147 and 0.536, respectively, implying that SE had a more significant positive effect on AP than AU.

The research findings suggest a significant and positive relationship between the constructs of the CoI and the unified theory of acceptance and use of technology (UTAUT 2) on student engagement, satisfaction, and performance in blended MOOCs. Specifically, the results indicate that the actual use of UTAUT 2 and students' engagement from CoI together significantly impact student satisfaction and perceived academic performance in blended MOOCs more than each construct standing alone.

9.3 The implications of the findings

At this juncture, the implications of the research findings about the design and implementation of blended MOOCs and blended learning in university education and how it can be applied in universities in the global south, sub-Sahara Africa and Ghana with similar characteristics to UCC shall be discussed.

9.3.1 Implication relating to the determinants of behavioural intention for blended MOOCs

The results indicate that the probability of students utilising blended MOOCs is higher when they perceive that they can attain effective learning outcomes (performance expectancy) and anticipate ease of use (effort expectancy). Institutions providing blended MOOCs should effectively convey the learning objectives of their courses to students, guarantee that the courses are congruent with the learners' objectives and that they comprehend how the courses can facilitate attaining those objectives and enhance their scholarly accomplishments. In addition, it is imperative for educational establishments providing blended MOOCs to prioritise the development of user-friendly and accessible courses. The results also indicate blended MOOCs are more likely to be utilised by students driven by hedonic motivation. Institutions providing blended MOOCs should consider incorporating gamification or gamified learning environment elements into their curricula.

Besides what has been discussed, the results indicate that the probability of students utilising blended MOOCs is higher when they perceive the course as valuable (task value). This finding suggests that establishments providing blended MOOCs should prioritise ensuring that their courses are pertinent and beneficial to their students. Furthermore, the results indicate that the probability of students utilising blended MOOCs is higher when they have previously established a routine of utilising online learning resources (habit). It is imperative for institutions that provide blended MOOCs to prioritise user-friendliness and facilitate diverse learning modalities for students while also enabling them to hone their proficiency in online learning tools. Finally, the research results indicate that students are more likely to use blended MOOCs when they perceive that their peers and instructors support them (social influence). Institutions providing blended MOOCs are recommended to establish a supportive environment that fosters open communication among students and instructors. This suggestion can be achieved by encouraging students to discuss their experiences online and in person.

In general, this investigation's results indicate that multiple variables impact the degree to which students are inclined to utilise blended MOOCs. Through comprehension of these variables, educational establishments can formulate and administer blended MOOCs that possess a higher probability of achieving success.

Here are some specific ways that institutions can apply these findings to their blended MOOCs and blended learning programmes:

- Ensure that the course is user-friendly and straightforward to navigate. This proposal entails utilising unambiguous and succinct terminology, furnishing a sequential set of directives, and employing uncomplicated technological tools.
- Facilitate occasions for learners to engage in exercises that involve the utilisation of digital learning resources. One recommendation is to incorporate instructional materials within the course platform, such as tutorials or interactive activities that require online learning tools.
- Developing well-designed courses is crucial. This proposal entails furnishing students with clear and succinct directives, employing various pedagogical exercises, and affording students' occasions to engage with the subject matter and their peers.
- Synchronise academic courses with the aspirations of the students. One recommendation involves a) the provision of clear learning objectives to students, b) assisting them in recognising their learning objectives, and c) affording them opportunities to contemplate and evaluate their learning experiences.
- Ensure that the courses are user-friendly and accessible. One possible recommendation is to offer clear and succinct guidance, employ uncomplicated terminology, and refrain from superfluous technical vocabulary.
- Facilitate avenues for students to communicate with their educators and classmates. One possible recommendation is implementing various strategies such as live online office hours, discussion forums, and student meetups. It is important to communicate to students the potential benefits of blended MOOCs to enhance their academic performances. A potential suggestion is to provide

perspectives on the instructional benefits of incorporating blended MOOCs, such as improved scholarly performance and increased information retention.

9.3.2 Implication relating to factors affecting the continued use of blended MOOCs

The findings suggest that the behavioural intention construct is a significant determinant of adopting blended MOOCs among students. It also suggests that the presence of facilitating conditions and the development of habits are crucial factors that influence the successful utilisation of blended MOOCs among students. It implies that students' adoption of blended MOOCs is contingent upon their behavioural intention. It is advisable for educational establishments offering blended MOOCs to give precedence to creating engaging syllabi that foster learners' drive to gain knowledge. Institutions that offer blended MOOCs should focus on making it more likely for students to use these classes.

It is advisable for educational institutions offering blended MOOCs to prioritise creating engaging course designs that foster students' innate drive to acquire knowledge. The findings also suggest that the presence of facilitating conditions, such as adequate technological accessibility and sufficient instructor support, plays a pivotal role in determining the level of adoption of blended MOOCs among students. It is essential for schools that offer blended MOOCs to make sure that their students have the tools they need to do well in these courses. Additionally, the result shows that students' habits significantly affect whether or not they sign up for blended MOOCs. It is vital for institutions that offer blended MOOCs to make sure that their classes are set up in a way that encourages people to use them regularly. Also, students must be able to fit these classes easily into their already-established schedules. According to Fitrianie et al. (2021) and Hu et al. (2020), the research shows that students' use of blended MOOCs can be affected by several things, such as their motivation, prior knowledge, experience, self-efficacy, trust, anxiety and hedonic motivation. Institutions should consider the factors mentioned in this study when designing and delivering blended MOOCs. In general, the present research outcomes indicate that educational establishments providing blended MOOCs ought to prioritise the development of captivating curricula, furnish learners with the tools for triumph, and motivate them to utilise these resources. Moreover, it is imperative for educational institutions that provide blended MOOCs to cater to the requirements of their students and foster a learning environment that motivates them to cultivate effective study practices.

The following are several concrete strategies academic institutions can use to implement these discoveries in their blended MOOCs.

- Motivating students to cultivate a routine of utilising the courses is recommended. This proposition entails implementing various strategies such as issuing prompts, providing rewards and fostering a communal atmosphere among the student body.
- Enhance the students' inclination to utilise blended MOOCs. One possible hint is to give students insights regarding the advantages of utilising these courses, including the capacity to acquire knowledge at a self-determined rate, the prospect of engaging with fellow students, and the possibility of attaining college credits.
- Furnish students with the necessary resources and assistance to effectively utilise blended MOOCs. One potential strategy for improving student outcomes is facilitating access to technological resources such as computers and the Internet, offering supplementary academic assistance and support services, and fostering a learning environment that promotes active inquiry and a willingness to seek assistance when necessary.
- Ensure that students have the necessary resources to succeed. One potential hint entails furnishing students with technological resources, such as laptops and tablets, or offering assistance from educators or colleagues.
- Ensure that students can effectively integrate the courses into their pre-existing schedules. One potential solution is providing courses during various time slots, or granting students the flexibility to progress through coursework at their preferred pace.

9.3.3 Implications relating to the effects of students' engagement within blended MOOCs

The findings suggest that the four presences of the CoI framework, namely teaching, cognitive, social, and learning presence, all significantly influence student engagement in blended MOOCs. Institutions offering blended MOOCs should focus on creating a learning environment that supports all four types of presence and time management skills. Again, institutions offering blended MOOCs should focus on designing courses that promote these four presences. The findings also suggest that learning presence has the strongest impact on student engagement, followed by cognitive, teaching and social presence. Institutions offering blended MOOCs should focus on creating an environment where students can learn from each other, work together, share their ideas, and get feedback from their peers and instructors. Additionally, the results show that the four presences of CoI explain 56.8% of the difference in how involved students are in blended MOOCs. This result is shown by the R square score of 0.568. The aforementioned statement posits that additional variables may influence student engagement, including attentiveness, academic rigour, and cognitive demands (Ginting, 2021). As student engagement is a complex concept, institutions providing blended MOOCs should broadly promote it. Here are some specific ways that schools can use these results in their blended MOOCs:

- Establish an educational setting that fosters the integration of all four presences. One possible recommendation is to facilitate avenues for student engagement through various means, such as fostering opportunities for peer-to-peer collaboration, promoting instructor-student interaction, and facilitating engagement with course materials.
- Promote the cultivation and maintenance of a robust teaching presence. Enhancement of this process can be achieved by the provision of explicit instructions and prompt feedback, the facilitation of meaningful discussions, and the responsiveness to the individual needs of students. Educators have the potential to employ multimedia resources to elucidate intricate concepts and offer practical illustrations, hence enhancing the applicability of the learning experience. Finally, offer instructional staff professional development opportunities to enhance their ability to design compelling and participatory instructional presentations.
- Foster the creation and preservation of a solid cognitive presence. Educational institutions can enhance cognitive engagement by formulating intellectually demanding tasks that foster the development of critical thinking skills and problem-solving abilities. In addition, it is plausible for educational institutions to offer supplementary materials to facilitate self-directed learning and foster

students' introspection over their learning journey. Another likely strategy is allowing students to engage in peer discussions regarding the subject matter, undertake exercises aimed at solving problems, and engage in introspection regarding their educational progress.

- Cultivate a strong social presence. With this idea, educational institutions have the potential to integrate collaborative endeavours, such as group projects or discussion forums. Additionally, students have the option to utilise social media platforms and various communication tools to foster a collective sentiment of community. Finally, instructors could set up online discussion groups, organise student get-togethers, and use social media to connect students and the instructor.
- Advocate for the initiation and continuation of a potent learning presence. This pertains to the learner's capacity to self-regulate their learning process. Educational institutions can facilitate this process by furnishing students with ample resources about effective time management and study techniques, implementing adaptable learning trajectories, and fostering a culture of self-directed learning wherein students are motivated to establish and oversee their educational objectives.
- Encourage interaction between students and the instructor. One potential approach is providing students with various avenues for peer-to-peer communication, such as collaborative assignments, online forums, group-based tasks, in-person meetings, or virtual office hours.
- Guarantee that the curriculum material is captivating and pertinent to the academic goals of the learners. This notion may involve the utilisation of interactive pedagogical methodologies, such as simulations and gamification, or providing opportunities for learners to employ their acquired knowledge to address genuine challenges in real-world contexts.
- Facilitate avenues for students to obtain guidance from their instructors. A plausible approach is to incorporate virtual office hours, establish discussion forums, or offer avenues for students to submit assignments for evaluation.
- Make learning a priority. This idea could involve letting students set goals, keep track of their progress, and get comments from their friends and instructor.

- Foster a collaborative learning environment where students can engage with their peers and the instructor to enhance their learning experience. One possible hint is to offer avenues for students to engage in peer-to-peer interaction, such as through collaborative project work, participation in online discussion forums, group assignments, facilitation of student meetups or attendance at virtual office hours.
- Offer assistance and motivation to students is crucial. One potential solution is providing tutoring services, establishing a collaborative platform for students to engage in inquiry and idea exchange, or furnishing students with constructive evaluations of their academic output.
- Offer students various avenues to obtain instructor feedback. One possible recommendation is to implement various strategies, such as providing synchronous virtual office hours, establishing online discussion boards, and facilitating the submission of assignments for constructive criticism.
- Encourage the establishment and maintenance of a robust social presence. One possible recommendation would be implementing various strategies, such as establishing virtual discussion boards, coordinating student gatherings, and leveraging social media platforms to facilitate communication between students and the instructor.
- Facilitate the cultivation of a conducive environment for learning. One possible hint would be to offer students the chance to establish objectives, monitor their advancement, and obtain evaluations from their peers and instructor.

9.3.4 Implications relating to the relationship between students' engagement and satisfaction or perceived academic performance in blended MOOCs

In blended MOOCs, the results show that student engagement significantly and positively affects how satisfied students are and how well they do academically. The claim above means that educational institutions that offer blended MOOCs should prioritise creating a learning environment that encourages active engagement from students, no matter what technology platform is used. The results show that student engagement has a more significant effect on student satisfaction than academic success. Even though there are few instant improvements in academic success, institutions that offer blended MOOCs should prioritise creating a pleasant, enjoyable, and rewarding learning environment for students. The study's findings show that student engagement explains around 41.3% of the variation in satisfaction with learning and 34.6% in academic performance, respectively, with R square values of 0.413 and 0.346. The statement above indicates that other factors affect students' satisfaction, such as engagement and conversation between students and instructors, how much time students spend on academic tasks, and how well they work with their peers (Grey & DiLoreto, 2016). According to Pham et al. (2021), the factors that affect academic success include but are not limited to learner characteristics, perceived usefulness, course material, course design, ease of use, and teaching ability.

Here are some specific ways that institutions can apply these findings to their blended MOOCs:

- Establish an educational setting that fosters active engagement and encourages student participation. One possible strategy for achieving this goal is to utilise engaging instructional methods, such as simulations and games, or to offer students more chances to collaborate on tasks, participate in peer discussions, and receive beneficial feedback from the instructor.
- Provide students with a favourable and captivating academic environment. One potential suggestion is to integrate engaging and interactive educational materials, such as simulations and games, that allow learners to apply their acquired knowledge in practical situations or provide them with a sense of independence in their learning journey.
- Furnish students with the essential resources and tools required to attain academic excellence. One possible approach is furnishing students with computer technology, tablet devices, opportunities for collaborative study groups, and supplementary learning resources.
- Provide educational guidance to instructors regarding efficient strategies for fostering dynamic student participation. One possible approach entails delivering pedagogical instruction to instructors regarding integrating active learning techniques, furnishing constructive evaluations, and cultivating a conducive learning environment.
- Establish an educational environment that fosters peer-to-peer learning and encourages collaborative efforts, particularly in group assignments. The proposed

strategy entails several measures, including the establishment of virtual discussion platforms, the formation of student cohorts, and the coordination of student meetings.

- Facilitate accessibility for students to ascertain the perspectives of their instructors. A proposed solution involves the implementation of diverse online communication channels, such as synchronous virtual office hours, digital discussion forums, and the facilitation of electronic submission of assignments to enable students to receive feedback.

9.3.5 Implications relating to the relationship between the actual use of blended MOOCs influences their engagement

The results show that actual usage of blended MOOCs significantly affects how engaged students are. It is suggested that institutions that offer blended MOOCs put the development and implementation of exciting courses at the top of their priorities. These courses should successfully involve students and make them want to use them. The results show that the path coefficient of 0.196 shows that actual use explains about 19.6% of engagement. This statement indicates that student engagement may also be affected by factors like what they already know, what motivates them, and how well they can manage their time. Based on the study's results, the R-squared value of 0.568 shows that actual use accounts for about 56.8% of the difference in engagement. The above argument indicates that educational institutions offering blended MOOCs should put the development and implementation of exciting programmes at the top of their priorities. This suggestion will make students more interested in the courses and more likely to use them.

Here are some specific ways that schools can use these findings to improve their blended MOOCs.

- Make sure the classes are created in a way that grabs and keeps the learners' attention. One possible way would be to use engaging teaching methods, like simulations and games, or to help students learn in groups.
- Encourage students to build a natural desire to learn and improve. One possible suggestion is to give students clear goals and objectives or make applying what they have learned to real-world problems easier.

- Give students the tools they need to succeed. One possible answer would be to give students access to technology like laptops and tablets or to have instructors or friends help them.
- Ensure students can fit the classes into their already-established plans is vital. One possible answer would be to offer classes at different times, such as in the evenings and early mornings, or to let students move through their homework at their own pace.

9.3.6 Implications relating to the combined effect of Actual use and students' engagement on their satisfaction or perceived academic performance in using blended MOOCs

Results show that how well learners use and participate in blended MOOCs significantly affects how satisfied they are and how well they do in school. It is important for schools that offer blended MOOCs to put the creation of exciting courses that encourage student participation and use at the top of their list of priorities. The study's results show that student engagement has a more significant effect on academic success and student satisfaction than just how well resources are used. Even though there are few instant improvements in academic performance, schools that offer blended MOOCs should put the creation of a friendly and fulfilling learning environment for students as their top priority. Also, the results show that the combination of visible usage and active engagement can explain more of the differences in student satisfaction and perceived academic performance than either variable alone. It is suggested that schools that offer blended MOOCs put the creation of exciting courses and get students to use them at the top of their list of priorities. The results show that the combination of actual use and participation can explain about 48.2% of the differences in how well students do in school and how satisfied they are. This statement suggests other factors affect how satisfied students are and how well they do in the classroom.

Here are some specific ways that institutions can apply these findings to their blended MOOCs:

- Make sure that the classes are made in a way that gets and keeps the pupils' attention and interest. One possible way would be to use engaging methods, like models and games, or to help students work together to learn.

- Encourage students to want to learn. One suggestion is to give students clear goals and objectives or give them chances to use what they have learned in real-world situations.
- Make it easy for students to find out what their instructors think. One possible suggestion is to use different tactics, like having synchronous virtual office hours, setting up online discussion groups, and letting students submit their work for constructive feedback.
- Ensuring students can fit the classes into their already busy plans is vital. One possible answer would be to offer classes at different times, like evenings and early mornings, or to give students the freedom to move through their classes at their own pace.

The results of this study show that several important factors affect how learners in blended MOOCs plan to act. The UTAUT2 and COI theoretical models entirely picture the many factors affecting student engagement, satisfaction and academic success. Instructors and instructional designers can use the results of this study to make blended MOOCs that involve students more, make them happier, and help them do better in school.

9.4 Recommendations

Based on the results of the study, many ideas can be put forward to help students in blended MOOCs be more engaged, satisfied, and perform well academically. This study's detailed analysis and findings yield theoretical, policy, practical, and research-based suggestions. These suggestions boost blended MOOC student engagement, satisfaction, performance and usage acceptance. Integrating these principles is crucial for improving education and creating a good learning environment.

Theoretical Recommendations

- Performance Expectancy and Learning Objectives: Instructors and instructional designers should emphasise technology-learning objective alignment. Ensuring students see technology as a tool for learning can boost engagement and satisfaction.

- Effort Expectancy and User-Friendly Design: Institutions should prioritise user-friendly technology platforms and give resources to improve students' view of technology ease. An easy-to-use interface can boost engagement.
- Social Influence and Community Building: Schools should make students and teachers feel supported. Encourage peer-to-peer interaction and collaborative learning to boost engagement and belonging.

Policy Recommendations

- Technology Integration and Accessibility: Policies should provide students with devices and reliable internet connectivity. Equity in technology can boost student participation and diversity.
- Pedagogical Training for Instructors: Educational Institutions should require professors to acquire pedagogical training. Teachers should learn how to establish an engaging and supportive learning environment in this programme.

Practical Recommendations

- Enhanced Teaching Presence: Instructors should prioritise clear instructions, well-organised course materials, and timely feedback. Teaching presence improves student comprehension and engagement.
- Fostering Social Interaction: Institutions should provide multiple ways for students and faculty to interact to create an optimal social setting. Online communities, group projects, and real-time discussions do this.
- Problem-Based Learning and Collaboration: Problem-based learning and group projects boost cognitive presence and engagement.
- Setting explicit Learning Goals: Instructors should set explicit learning goals and give students feedback. A unified purpose and goals can improve learning.

Research Recommendations

- Continuous Evaluation and Assessment: Researchers should test student engagement, satisfaction, and academic performance strategies. To discover the most effective methods, ongoing assessment is essential.

- Technology Use Analysis: More research should focus on the technology use and student engagement factors that most affect blended MOOC academic success. This can guide student support and interventions.

Incorporating these principles into mixed MOOC design, implementation, and governance can enhance learning. Institutions can better prepare students for digital education and improve blended MOOCs by addressing theoretical, policy, practical, and research elements.

Based on the results of the study, many ideas can be put forward to help students in blended MOOCs be more engaged, satisfied, and perform well academically. This section is mainly about these specific things that educators and instructional designers can help students to develop good habits for using technology and being involved in a class by implementing these ideas. Implementing these suggested recommendations is crucial in improving academics and giving greater satisfaction.

The results about what makes people want to do something suggest that instructors and instructional designers should think about the following things when implementing blended MOOCs.

- Performance expectancy indicates that students are more likely to participate in a blended MOOC if they think the technology will help them to reach their learning goals and aims.
- According to effort expectancy, a student's chance of participating in a blended MOOC is linked to how easy they think the technology is, and how much work they think it will take in its use.
- The likelihood that a student will participate in a blended MOOC is affected by social factors, especially how their friends and instructors see the worth and frequency of technology use.
- Research shows that a student's regular use of technology is a good indicator of whether or not they will participate in a blended MOOC.
- The hedonic drive plays a significant role in whether or not a student will join a blended MOOC. Students are more likely to participate in fun and exciting tasks.
- Students are more likely to participate in a blended MOOC if they think the learning tasks are helpful, engaging and relevant to them.

In blended MOOCs, instructors and course designers should create an environment that encourages positive attitudes about effort, performance, hedonic motivation, social influence, task value and habits. This guide will help students be more engaged, satisfied, and good at their work. The above plan can be carried out using suitable educational design methods, setting clear expectations, and creating a good learning environment. Also, blended MOOCs should improve students' engagement, satisfaction and success by prioritising the factors that are good predictors of future behaviour. Educators and instructional designers must give careful thought to the design of blended MOOCs in order to improve how students see the usefulness and ease of use of the technology, the relevance of the course, the social support from peers and instructors, the inclusion of gamification elements, and the formation of habits that encourage regular participation.

Concerning the factors that affect the long-term use of blended MOOCs, it is suggested that instructors and MOOC developers focus on increasing students' desire to use MOOCs, creating the necessary conditions for their use, and encouraging the formation of habits to increase the effective use of MOOCs. Educational institutions should help students to use MOOCs by giving them the tools and help they need. Also, schools should encourage the development of habits that encourage the use of technology and build classes that align with what students want to do and how they want to act.

Concerning how the four presences of the community of inquiry affect how engaged students are in blended MOOCs, it is recommended that instructors and designers of such blended MOOCs pay attention to the following suggestions:

- Put the design of teaching presence at the top of their list of priorities. This guide ensures that instructions are clear, that course materials are well-organised, and students get feedback when needed.
- To create an ideal social setting, it is best to give students and instructors ways to talk to each other and the instructor. This hint can be done in several ways, such as through online communities, group projects and real-time talks.
- It is best to give students problem-based learning tasks or group projects, requiring them to participate and work together to increase cognitive presence.
- Students should encourage a shared sense of purpose and goals to improve the learning present. This suggestion can be achieved by setting clear learning goals and giving students time to think and get feedback.

Given that students' engagement and satisfaction with blended MOOCs are related, instructors and course designers should prioritise using strategies that get students more involved. Some of these might be engaging tasks, ways for peers to work together, and ways to get feedback. Also, it could be helpful for students to have clear goals for their education and learning experiences tailored to their hobbies and goals.

Based on the suggestions about the link between students' engagement and perceived academic performance in blended MOOCs, instructors and course creators must develop effective ways to get students more involved. This plan calls for engaging and collaborative teaching methods, delivering personalised feedback and help, and merging technology resources to improve the learning experience. Also, instructors and instructional designers must constantly evaluate and assess how well these strategies work to keep students interested and improve their academic performance. Also, it is recommended that collaborative and engaging learning activities be used, that students be given quick and helpful feedback, and that students be urged to participate and learn actively to get them more involved and help them do better in class.

Because students are more engaged with blended MOOCs when they use technology, instructors and course designers should focus on increasing student engagement and promoting the practical use of technology. This suggestion will promote satisfaction among students with blended MOOCs. Furthermore, it can be achieved by using interactive teaching methods, giving students feedback often, and adding technology tools that align with the course's goals. Some of these strategies include using interactive tools, giving students chances to learn together, and creating engaging course content (Jung, 2018). To ensure that students get the most out of their blended MOOC experience, it is also essential to keep reviewing and tracking student engagement and satisfaction.

As for the link between actual usage and how well students do when using blended MOOCs, the researcher suggests that instructors consider employ blended MOOCs and other EdTech in their classes. Instructors should encourage students to use technology more often and engage more in class. This idea can be implemented by giving students the necessary resources and support, including clear directions, comments, and online conversation forums. Some other things that could be done include the following:

- Encouraging students to actively use technology to connect with course material and talk to their peers and instructors could help them do better in class.
- Giving students resources and support to develop and improve their engagement skills, such as time management and motivation.
- Finding out what parts of actual usage and student engagement are most strongly related to academic success in blended MOOCs so that more targeted interventions and support can be made for students.

9.5 Significance and Contribution of the Study

Based on the research question and the frameworks used (CoI and UTAUT 2), this research can make several possible contributions. These contributions are divided into theoretical and practical.

9.5.1 Theoretical contributions

This research has the potential to contribute significantly to the field of e-learning, encompassing online and blended learning, MOOCs and blended MOOCs, through various means. The present research endeavour has the potential to showcase the efficacy of blended MOOCs as a pedagogical approach. The result of the study contributes to the existing body of studies on EdTech, e-learning and MOOCs by investigating students' usage acceptance, engagement, satisfaction and perceived academic performance in blended MOOCs by applying established theoretical frameworks. The study will help to create a more complex, multi-dimensional framework for understanding how students are engaged, how satisfied they are, and how they perceived to well do in blended MOOCs. Student engagement, linked to better learning results, is a complex concept that are usually measured with many dimensions, such as behavioural, cognitive, collaborative, emotional and social engagement. However, using the Community of Inquiry (CoI) model as a guide, this study gives other picture of the factors that affect student engagement in blended MOOCs. This study can also find new ways to get students interested that may have yet to be looked at in earlier studies. For example, the role of technology and learning presence's strategies in getting students interested are yet to be accepted by some researchers of the community of inquiry, hence the inability of some of the originators to accept learning presence as one of its presences.

Again, this study will help us to learn more about how the four presences of the Community of Inquiry model and the seven factors of the UTAUT 2 model affect student behaviour in blended MOOCs. This research can look at how the different factors of the UTAUT 2 model (like performance expectations, effort expectations, social influence, and facilitating conditions) interact with the four presences of the CoI model (social, cognitive, teaching, and learning presence) through engagement to affect how students act in blended MOOCs. By examining how these factors interact, this study can learn more about the processes that drive student engagement, satisfaction, and academic performance.

This study expands on the existing literature on blended MOOCs by examining the specific factors that impact student engagement, satisfaction and perceived academic performance in this setting. Blended MOOCs embody an innovative educational methodology that integrates the benefits of MOOCs with traditional face-to-face teaching. Additional investigation is necessary to examine the variables contributing to scholastic performance in this situation. The result of this study will enable us to address the current gap in knowledge by investigating the various factors that influence students' engagement, satisfaction and perceived academic performance in blended MOOCs. A subsequent inquiry about this research should examine the importance of peer engagement, instructor participation, and technological integration.

Ultimately, this research initiative will provide noteworthy suggestions for educators, leaders and decision-makers who aim to integrate blended MOOCs into their educational practices to enhance student learning and success. The current study holds promise for aiding educators, administrators, and decision-makers in maximising the efficacy of blended MOOCs in bolstering student engagement, satisfaction, and perceived academic performance. This suggestion can be realised by identifying key determinants that impact student engagement, satisfaction and perceived academic performance in said educational settings.

9.5.2 Practical contributions

The current investigation holds promise for enriching the education domain by showcasing the effectiveness of blended MOOCs in augmenting scholarly performance and cultivating higher levels of satisfaction among learners. The present research holds the potential to investigate the influence of students' inclination towards utilising blended MOOCs and their degree of engagement with such courses on their academic satisfaction and performance. The results of this inquiry have the potential to elucidate the factors underlying the preference for and adoption of blended MOOCs among students from Ghana. The aforementioned concept holds promise in enabling the identification of approaches to improve the effectiveness of blended MOOCs regarding student performances. The present research holds promise in elucidating the approach and justification underlying students' adoption and engagement in blended MOOCs, thus enabling the identification of tactics to augment their effectiveness.

The focus of this study pertains to the population of students presently enrolled in a university located in Ghana. Through an examination of blended MOOCs, this investigation has enabled us to gain significant insights into the efficacy of this approach in enhancing student engagement, satisfaction and academic performances. In addition to the aforementioned potential accomplishments, this study has the potential to contribute to the advancement of future research in Ghana about blended MOOCs. Examining the diverse elements that impact how these students engage with blended MOOCs may contribute to our comprehension. These characteristics may encompass the availability of technology, societal norms and expectations around digital education, and additional contextual elements particular to Ghana. This study has the potential to enhance the accessibility of blended MOOCs in Ghana, hence facilitating a more seamless engagement with this particular learning method for a larger population. By examining blended MOOCs, this study has contributed to our understanding of how these courses can enhance accessibility to high-quality education for a broader range of students compared to traditional in-person classrooms. Consequently, blended MOOCs could elevate the overall educational standards within the nation and the sub-region. The findings of this study indicate that students exhibit a significant inclination towards utilising blended MOOCs due to their exposure to several advantages associated with these courses:

1. Unlike traditional face-to-face instruction, blended MOOCs offer a more comprehensive range of learning tools and methodologies.
2. They provide a platform for students to engage with peers and professionals from around the globe who share their disciplinary interests.

3. The study has identified that blended MOOCs can serve as a cost-efficient means of delivering education without compromising quality.

This study has the potential to influence the higher education system in Ghana substantially, as it aims to enhance the accessibility and affordability of quality education. This study proposes the implementation of blended MOOCs as a viable solution to expand the reach of high-quality, affordable higher education to a larger population. The results of this study should compel educational administrators in Ghana to reassess and enhance existing educational methodologies.

Some of the other possible contributions to study that this thesis could make are:

1. The results of this study could help us to learn more about the things that affect students' willingness to use blended MOOCs and how much they participate in them.
2. This study's results could help develop ways to improve how blended MOOCs are designed and taught.
3. The results of this study could make blended MOOCs more valuable as a way to learn.
4. The results of this study could help to shape how future research on blended MOOCs is done.

9.6 Further Research

In this section, the researcher highlights some areas for further studies because of the findings of the study. These proposed research directions are aimed at illuminating the relationships between blended MOOCs and various measures of student engagement, satisfaction, and academic performance. Research in these areas can help inform the creation of guidelines and methods for enhancing the quality of online education.

1. This study's quantitative technique was limited; thus, future research should use qualitative methods better to understand students' perceptions and experiences with blended MOOCs. Qualitative methods, including open-ended surveys, interviews, and focus group discussions, can reveal many elements affecting students' blended MOOC experiences and satisfaction, such as motives, preferences, and issues with blended MOOCs. Researchers can better understand students' opinions and experiences by combining quantitative and qualitative

information to guide targeted interventions and blended MOOC design and delivery improvements.

2. Investigating how the four presences of the Community of Inquiry framework—cognitive, social, teaching and learning—influence participation, satisfaction, and performance in blended MOOCs. While this study's results suggest that all four presences (cognitive, social, teaching, and learning from the Community of Inquiry) influence participation, satisfaction, and academic performance, more investigation into their relative importance is warranted. More nuanced insights into the effects of each presence on student engagement, satisfaction, and performance in blended MOOCs will be provided by this study. For instance, instructional design can be informed by research into which methods of instruction or types of learning activities are most effective at increasing students' interest and satisfaction. With the results of this suggestion, blended MOOCs can be designed and supported more precisely to meet the needs of their students.
3. Exploring how active engagement in a blended MOOC moderates student satisfaction and perceived academic performance and the other four Community of Inquiry presences. This study concludes that active participation by students mediates the connection between CoI presences and students' satisfaction and academic performance. More research into this mediation process is needed to comprehend student engagement's role in the CoI-outcomes nexus fully. This insight can inform the design of interventions and strategies to raise participation, satisfaction, and performance in blended MOOCs. Again, the results of this study shed light on the mechanisms connecting the Community of Inquiry framework's elements with students' engagement and their outcomes.
4. Analysis of how each component of UTAUT affects students' intentions to use blended MOOCs in their future behaviour. This study isolated seven variables from the UTAUT that predict students' intent to participate in blended MOOCs. The study results show that the seven components of UTAUT affect future behaviour. Understanding the mental processes and motivations that drive students to adopt blended MOOCs would allow for developing more effective interventions and strategies to increase tech adoption. The mechanisms and processes by which these factors affect students' intent to use blended MOOCs

can be investigated in greater depth in future studies. With this information, interventions that are more likely to succeed in increasing enrolment and engagement with blended MOOCs can be created.

5. Considering factors like technical support, access to resources, and prior experience with online learning, this study investigates the role of facilitating conditions, habits, and behavioural intention as predictors of the actual use of blended MOOCs among students. Results from the study point to the importance of facilitating conditions, habits, and behavioural intention in influencing students' actual use of blended MOOCs. The specific factors within facilitating conditions (such as technical support, resource availability, and prior experience with online learning) and habits (such as frequency of use) that predict the actual usage of blended MOOCs can be explored in further research. Such a study's findings can inform the development of infrastructure to facilitate increased usage and remove obstacles. Again, by gaining an awareness of these indicators, schools and MOOC providers can pinpoint problem areas and work towards bettering blended MOOCs for students.
6. The results of this study stress the significance of students' actual use of blended MOOCs in determining their level of engagement. The impact of technology adoption, learner characteristics, and course design features on student participation in blended MOOCs is investigated. In order to create compelling learning experiences, educators must have a firm grasp on the factors that affect student engagement in blended MOOCs. Additional research can examine the role of technology adoption, learner characteristics (such as motivation, self-regulation skills and learning styles) and course design features (such as interactivity personalised learning) in fostering student engagement. By delving into such a study, educators and designers of blended MOOCs could better meet the needs of their students. Again, such an in-depth analysis will give educators a bird's-eye view of the factors that influence student participation, leading to better decisions about curriculum development.
7. According to the results of the study, blended MOOCs have a significant effect on students' engagement, satisfaction and academic performance. The effects of actual blended MOOC use on these variables over time should be studied.

Furthermore, students' long-term success in blended MOOCs depends on teachers and support staff having a firm grasp on how student engagement, satisfaction, and performance change over time. Understanding the lasting effects and reliability of these variables requires a longitudinal study. Moreover, researchers can learn more about the durability of outcomes like student engagement, satisfaction, and performance by conducting longitudinal studies. Thus, longitudinal studies should be conducted to learn more about the effects of blended MOOCs on students' experiences that evolve over time. Such a study would shed light on the potential advantages and drawbacks of blended MOOCs for students' future academic success.

8. Examining instructor training quality: The success of blended MOOCs heavily depends on instructor training quality (Boga & McGreal, 2014; Radovan & Kristl, 2017). Understanding the significance of instructor competence in blended learning environments can be gained through research into the effects of instructor training programmes on the four presences from the Community of Inquiry framework, student engagement, and overall course satisfaction. Blended MOOCs are most successful when taught by teachers who have received extensive training in online pedagogy and the use of technology in the classroom. Research in this area can help institutions understand why spending money on teacher training is important to boost student outcomes.
9. Explore hedonic motivation for blended MOOCs: The use of gaming elements is becoming increasingly common as a means of increasing interest (Li et al., 2021). To better understand its applicability and potential impact, researchers should examine it in the context of blended MOOCs. In order to increase participation and retention in blended MOOCs, it is helpful to have a firm grasp on what makes gamification successful.
10. Investigate demographic factors: Individual differences in students can affect how they engage with blended MOOCs (Fellman et al., 2020). UTAUT and CoI factors and their outcomes can be better shaped by analysing the connections between demographic factors. This is because not all students have the same experiences with technology and online learning. Further studies should be conducted on how demographic factors like gender, age, level of experience, programme of study,

digital literacy, and motivation impact acceptance, use, student engagement, satisfaction and performance in blended MOOCs. This recommendation is made because, although demographic characteristics were not examined in this study, different demographic groups may acceptance, use and engage with blended MOOCs differently. Investigating how demographic factors may impact students' acceptance, engagement and learning outcomes can provide insights into how to cater for diverse student groups and design blended MOOCs that are inclusive and accessible to all. Furthermore, individualised methods that are adaptable to a wide range of student characteristics could be developed by studying this phenomenon.

11. Analysing the distribution of students' responses to statements: A study should be conducted to identify patterns or trends on the 5-point Likert scale statements for each construct. This suggestion is based on the finding that, on average, students' responses to statements on a 5-point Likert scale for each construct had over 80% agreed and strongly agreed. Researchers can identify patterns or trends in students' perceptions by analysing the distribution of responses for each construct. This suggestion could help educators understand students' attitudes towards different aspects of blended MOOCs and develop strategies to address any areas of concern.
12. Cross-cultural comparison: An examination of cultural influence on student in blended MOOCs is needed. How much students participate in EdTech, online learning or blended MOOCs can depend on their culture. For instance, African students' cultural background could affect how much they contribute, how satisfied they are, and how well they do. More research could be done to determine how culture affects how much African students participate in blended MOOCs. Such study could also compare the impact of the four presences in blended MOOCs between university students in Africa and other regions to see if cultural differences exist in their perceptions and experiences with blended MOOCs. Examining how different cultural backgrounds impact the efficacy of the CoI and UTAUT in engaging African university students would also be a worthwhile area of study, considering the vast cultural diversity present on the continent.
13. Generalisations of the findings: The call for further research to investigate the findings to other populations or educational contexts is rooted in the notion that

the outcomes of this study may lack universal applicability. Through an investigation into the generalisability of these findings, scholars can ascertain the extent they apply to diverse student populations or alternative educational contexts. This proposal has the potential to assist educators in comprehending the practical application of these discoveries within their respective settings, thereby enhancing student performances.

14. Examine student engagement against indicators of student satisfaction and academic academic: This call for research aims to investigate the correlation between student engagement and distinct indicators of student satisfaction and academic performance. This proposition is grounded on the discovery that student engagement impacts students' satisfaction levels and academic performance. Examining the correlation between student engagement and particular satisfaction and performance metrics can aid researchers in comprehending the impact of engagement on said outcomes. This call for research has the potential to assist educators in formulating tactics aimed at augmenting student engagement, as well as enhancing satisfaction and student performance.
15. The role of technology: An investigation of the role of technology in supporting the four presences in blended MOOCs and how it affects student engagement, satisfaction and performance should be conducted. Again, given the varying levels of technology infrastructure across Africa, it would be interesting to study how this affects the development of the Community of Inquiry and student engagement in blended MOOCs among the various digital divide– types (gender divide, social divide, universal access divide), or stages (economic, usability, and empowerment).
16. The impact of pedagogical approaches: A study of the impact of different pedagogical approaches on the four presences and student engagement in blended MOOCs should be done. Again, further research could focus on the role of the instructor in fostering student engagement, satisfaction, and performance in blended MOOCs, including their impact on the development of the Community of Inquiry.
17. Conduct longitudinal study: Doing a longitudinal study to examine how students' views and actions change over time: This suggestion is based on the idea that

students' thoughts and actions may change as they learn more about blended MOOCs. With a comprehensive study, researchers can see how students' thoughts and actions change over time. This idea could help instructors to determine how students' experiences with blended MOOCs change over time and develop ways to help them learn. The study has shown that the four presences of the Community of Inquiry affect student engagement. More studies could examine how blended MOOCs affect student retention and completion rates in African settings. This type of studies would help determine the effectiveness of blended MOOCs in engaging and keeping African university students interested.

18. Investigate the effectiveness of assessment methods: Blended MOOCs have attracted substantial attention and widespread acceptance as a versatile and inclusive mode of education. The focus of this recommended study is to explore the effects of the various evaluation methodologies on student engagement, satisfaction, and performance in the setting of blended MOOCs, considering the rapid progress of technology. This recommendation examines to explore the potential advantages and disadvantages of several assessment techniques, such as self-assessment, peer assessment, and exams, and their impact on student academics in blended MOOCs.
19. Instructional design strategies examination: This study did not directly examine instructional design strategies, but the design of the course and its learning materials can significantly impact student engagement, satisfaction, and performance. For instance, the research could investigate the impact of multimedia content, gamification elements, or peer-to-peer interaction and collaboration on student engagement and learning outcomes in blended MOOCs.

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LIST OF APPENDICES

APPENDIX A: APPENDIX A: ETHICAL CLEARANCE CERTIFICATE FROM UKZN

UNIVERSITY OF KWAZULU-NATAL
INYUVESI YAKWAZULU-NATALI

10 November 2020

Mr John Edumadze (219091722)
School Of Education
Edgewood Campus

Dear Mr Edumadze,

Protocol reference number: HSSREC/00002112/2020
Project title: An investigation of blended Massive Open Online Courses on students learning and academic performance
Degree: PhD

Approval Notification – Expedited Application

This letter serves to notify you that your application received on 29 September 2020 in connection with the above, was reviewed by the Humanities and Social Sciences Research Ethics Committee (HSSREC) and the protocol has been granted **FULL APPROVAL** on the following condition:

Any alteration/s to the approved research protocol i.e. Questionnaire/Interview Schedule, Informed Consent Form, Title of the Project, Location of the Study, Research Approach and Methods must be reviewed and approved through the amendment/modification prior to its implementation. In case you have further queries, please quote the above reference number. PLEASE NOTE: Research data should be securely stored in the discipline/department for a period of 5 years.

This approval is valid until 10 November 2021.
To ensure uninterrupted approval of this study beyond the approval expiry date, a progress report must be submitted to the Research Office on the appropriate form 2 - 3 months before the expiry date. A close-out report to be submitted when study is finished.

All research conducted during the COVID-19 period must adhere to the national and UKZN guidelines.

HSSREC is registered with the South African National Research Ethics Council (REC-040414-040).

Yours sincerely,

Professor Dipane Hlalele (Chair)

/dd

Humanities and Social Sciences Research Ethics Committee
Postal Address: Private Bag X54001, Durban, 4000, South Africa
Telephone: +27 (0)31 260 8350/4557/3587 **Email:** hssrec@ukzn.ac.za **Website:** http://research.ukzn.ac.za/Research-Ethics

Founding Campuses: Edgewood Howard College Medical School Pietermaritzburg Westville

INSPIRING GREATNESS

APPENDIX B: APPLICATION FOR PERMISSION TO CONDUCT RESEARCH AT UCC

University of Cape Coast,
Directorate of ICT Services
IT Traning and Support Services
Sam Jonah Library Basement #1 UCC, Cape Coast
Wednesday, 3 June 2020

The Dean,
Students' Affairs,
University of Cape Coast Cape Coast, Ghana.

Dear Sir,

PERMISSION FOR DATA COLLECTION

I am pursuing a PhD (Computer Science Education) at the University of KwaZulu-Natal, South Africa. As part of my research, I am soliciting for the approval from your office to use the students at the University of Cape Coast as a sample for the data collection of the dissertation. The title of the work is "The influence of blended Massive Open Online Courses (MOOCs) on students' learning and their academic performance".

Since the 2016/2017 academic year, the IT Training and Support Service (ICT Centre) has introduced one credit hour course for all level 100 students entitled "ITS 101–Information Technology Skills". The said course is a blended Course with a one-hour practical session a week at the ICT Centre and a self-paced session using Alison's MOOC platform where students watch videos, participate in discussion forums and write online formative and summative assessments. The study aims to assess students' experience in the instructional delivery system (MOOC) and instructional delivery strategy (blended MOOC) and whether the said system and strategy enhance students' learning, satisfaction and academic performance. The outcome of the study will fill the knowledge gap and aid in policy formulation of blended MOOC in higher education institutions globally. Since electronic learning has not taken root in the University of Cape Coast, the outcome will be used to ascertain students' readiness to engage in this instructional delivery mode.

I intend to administer questionnaires to students who have had experience in using blended MOOC at UCC. Such students will be randomly selected among those who will opt to participate in the research that will last for 20 minutes. As a way of addressing ethical concerns, participants will be made to take notice of the following:

- Participation in this research project will not yield any monetary benefits except airing their views that share policy on blended MOOC in UCC.
- Participants are encouraged to attempt all questions.
- They are to respond to each question in the manner that will reflect their view.
- Participants' identity will not be divulged under any circumstance.

- All participants' responses will be treated with strict confidentiality.
- Participation is voluntary; thus, they are free to withdraw at any time without negative or undesirable consequences to them.
- Data of responses will be stored in the Dropbox cloud storage with the password known only to my supervisor and myself for a maximum period of five years and thereafter destroyed.

My Contacts: Cell: 024 394 2749 or 0506799047 and Email addresses: jedumadze@ucc.edu.gh or 219091722@stu.ukzn.ac.za. This study is supervised by Prof Desmond Govender, Te1: +27031 260 3428, Email address: govenderd50@ukzn.ac.za.

From the discussion so far, I would be most grateful if you grant permission for the said exercise to be conducted. I hope to receive a favourable response to this request. Thank you.

Yours faithfully,

[redacted]

John K.E. Edumadze

APPENDIX C: APPROVAL LETTER FROM DEAN OF STUDENTS' AFFAIRS, UCC

UNIVERSITY OF CAPE COAST
CAPE COAST, GHANA
OFFICE OF THE DEAN OF STUDENTS

Telephone: 233-3321-32440/4 & 32480/3 Ext. 226
233-3321-33707 (Direct)
Fax: 233-3321-33707
Email: studentsaffairs@ucc.edu.gh

UNIVERSITY OF CAPE COAST
CAPE COAST, GHANA

Our Ref: ODS/ODS/VOL.2/15
Your Ref

12th June, 2020.

Mr John K.E. Edumadze
Directorate of Information and Communication Technology Services
UCC

Dear Sir,

RE: PERMISSION FOR DATA COLLECTION

We refer to your letter dated 3rd June 2020, on the above subject matter.

Approval is given for you to use the students of the University of Cape Coast as sample for data collection of your dissertation.

Thank you.

Yours faithfully,

[redacted]

STUDENTS
UNIVERSITY OF CAPE COAST
CAPE COAST

PROF. EUGENE K.M. DARTEH
DEAN

APPENDIX D: INFORMED CONSENT FOR STUDENTS

University of Cape Coast,
Directorate of ICT Services
IT Training and Support Services
Sam Jonah Library Basement #1
UCC, Cape Coast

Wednesday, 3 June 2020

Dear Student,

A REQUEST FOR YOUR PARTICIPATION

I am pursuing a PhD (Computer Science Education) at the University of KwaZulu-Natal, South Africa, with these contacts(Cell: 024 394 2749 or 0506799047 and Email addresses: jedumadze@ucc.edu.gh or 219091722@stu.ukzn.ac.za. Prof Desmond W. Govender is supervising me with these contacts (Te1: +27 031 260 3428, Email address: govenderd50@ukzn.ac.za).

You are invited to consider participating in a study involving research (An investigation of blended Massive Open Online Courses (MOOCs) on students' learning and academic performance). The aim of this research is to assess students' experience in the instructional delivery system (MOOC) and instructional delivery strategy (blended MOOC) and whether the said system and strategy enhance students' learning, satisfaction and academic performance. You are being invited to participate in this research since you have participated in a blended MOOC at this university and thus have the requisite experience.

Blended MOOC is an instructional delivery that combines UCC classroom courses supplemented with the MOOC platforms such as Alison, Coursera, Edx and Saylor.
The study will involve you filling out a questionnaire that will take you 20 minutes. The study aims to fill the knowledge gap and aid in the policy formulation of blended MOOCs in higher education institutions globally. Since electronic learning is yet to take root in the University of Cape Coast, the outcome will be used to ascertain students' readiness to engage in this instructional delivery mode. If you accept to participate in the research, I would like to draw your attention to the following:

1. Your participation in this research project will not yield any monetary benefits except airing their views that share policy on blended MOOC in UCC.
2. You are encouraged to attempt to all questions.
3. Please respond to each question in a manner that will reflect your personal opinion.
4. Your identity will not be divulged under any circumstance.
5. You should be mindful of the fact that there is no right or wrong answer.
6. Your responses will be treated with strict confidentiality.
7. Participation is voluntary; therefore, participants are free to withdraw at any time without negative or undesirable consequences to them.

8. You will not be under any circumstances forced to disclose what they do not want to reveal.
9. Data of your responses will be stored in the Dropbox cloud storage with the password known only to my supervisor and myself for a maximum period of five years and thereafter destroyed.

Given this, I would be most grateful if you accept this invitation to participate in the study by filling the questionnaire for this research. You can do so by firstly signing the consent letter attached. Thank you.

Yours faithfully,

[redacted]

John K.E. Edumadze

____

CONSENT

I, _________________________________ (Name) have been informed about the study entitled (The influence of blended massive open online courses on students' learning and their academic performance) by (provide name of researcher/fieldworker).
I understand the purpose and procedures of the study.
I have been given an opportunity to answer questions about the study and have had answers to my satisfaction.
I declare that my participation in this study is entirely voluntary and that I may withdraw at any time without affecting any of the benefits that I usually am entitled to.
I have been informed about any available compensation or medical treatment if an injury occurs to me as a result of study-related procedures.
If I have any further questions/concerns or queries related to the study, I understand that I may contact the researcher at (provide details).
If I have any questions or concerns about my rights as a study participant, or if I am concerned about an aspect of the study or the researchers then I may contact:

HUMANITIES & SOCIAL SCIENCES RESEARCH ETHICS ADMINISTRATION
RESEARCH OFFICE, WESTVILLE CAMPUS
GOVAN MBEKI BUILDING

Private Bag X 54001
Durban
4000
KwaZulu-Natal, SOUTH AFRICA
Tel: 27 31 2604557 - Fax: 27 31 2604609
Email: HSSREC@ukzn.ac.za

_____________________ _____________________

Signature of Participant **Date**

APPENDIX E: LANGUAGE EDITOR'S CERTIFICATE

UNIVERSITY OF CAPE COAST
COLLEGE OF HUMANITIES AND LEGAL STUDIES
FACULTY OF ARTS
DEPARTMENT OF COMMUNICATION STUDIES

Tel: 03321-30944
Email: dcs@ucc.edu.gh
Our Ref:
Your Ref:

University Post Office
Cape Coast, GHANA

30th June, 2023

Certificate of Editing

This is to certify that the doctoral thesis "An Investigation of Blended Massive Open Online Courses on Students' Learning and Academic Performance" **by** John Kwame Eduafo Edumadze has been thoroughly proofread and edited for clarity in expression, word order, spelling, punctuation, vocabulary and grammar.

Wincharles Coker, PhD

Editor & Senior Lecturer
Writing Unit
Department of Communication Studies
College of Humanities and Legal Studies
University of Cape Coast, Ghana
Email: wcoker@ucc.edu.gh

APPENDIX F: TURNITIN REPORT

AN INVESTIGATION OF BLENDED MASSIVE OPEN ONLINE COURSES ON STUDENTS' LEARNING AND ACADEMIC PERFORMANCE

ORIGINALITY REPORT

9%	7%	5%	3%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	www.researchgate.net Internet Source	1%
2	researchspace.ukzn.ac.za Internet Source	1%
3	uis.brage.unit.no	<1%

APPENDIX G: QUESTIONNAIRES

The influence of blended Massive Open Online Courses on student's learning and their academic performance

Introduction

Massive Open Online Courses (MOOCs) are free online courses that can be enrolled and taken by anyone and provided by MOOC Providers such as Alison, Coursera, Edx, Saylor, etc. Universities worldwide are using MOOC courses to supplement their regular campus-based programme. You are participating in the survey because you took a course supplement or complement with a MOOC platform such as Alison, Saylor or Edx. The instructional delivery for the courses named above is blended MOOC. Blended MOOC is a form of blended learning that lies between purely face-to-face and purely online e-learning continuum. Kindly be truthful and report purely from your experience and observation.

Objective: This questionnaire is aimed at accessing your experiences in using the content of the said MOOCs as open educational resources for the UCC courses mentioned. Your response will help the University in policy formation in this regard.

Note of Confidentiality: Your confidentiality is fully guaranteed.

Section A: Demographic Characteristics (Use an √ to indicate your choice)

1. Sex: a. Male [ ] b. Female [ ]
2. Programme Grouping:
   a. STEM—Science, Technology, Engineering & Mathematics [ ]
   b. Non-STEM—Business. Law, Arts and Social sciences | Humanities [ ]
3. Level at which you last used blended MOOC:
   a. 100 [ ]
   b. 200 [ ]
   c. 300 [ ]
   d. 400 [ ]
   e. 500 [ ]
   f. 600 [ ]
   g. 700 [ ]
   h. 800 [ ]

Section B: Community of Inquiry (CoI) model for blended MOOC

Please indicate your level of agreement in each of the following statements. The levels of agreement are:

a) strongly agree SA, b) agree A, c) undecided U, d) disagree D, and e) strongly disagree SD.

Statements	**SA**	**A**	**U**	**D**	**SD**
4. Learner Presence (LP)					
a. *Motivation (M)*					
i. LP1M1: In a class like this, I prefer course material that really challenges me so I can learn new things.					
ii. LP2M2: In a class like this, I prefer course material that arouses my curiosity, even if it is difficult to learn.					
iii. LP3M3: The most satisfying thing for me in this course is trying to understand the content as thoroughly as possible.					

Statements	SA	A	U	D	SD
iv. LP4M4: I want to do well in this class because it is important to show my ability.					
v. LP5M5: Getting a good grade in this class is the most satisfying thing for me right now.					
vi. LP6M6: The most important thing for me right now is improving my overall grade point average, so my main concern in this class is getting a good grade.					
b. *Self-Efficacy for Learning (SEL)*					
vii. LP7SEL1: I'm certain I can understand the most difficult material presented in the readings for this course.					
viii. LP8SEL2: I'm confident I can understand the basic concepts taught in this course.					
ix. LP9SEL3: I'm confident I can understand the most complex material presented by the instructor in this course.					
x. LP10SEL4: I'm certain I can master the skills being taught in this class.					
c. *Metacognitive Self-Regulation (MSR)*					
xi. LP11MSR1: When reading for this course, I make up questions to help focus my reading.					
xii. LP12MSR2: When I become confused about something I'm reading for this class, I go back and try to figure it out.					
xiii. LP13MSR3: If course materials are difficult to understand, I change the way I read the material.					
xiv. LP14MSR4: Before I study new course material thoroughly, I often skim it to see how it is organised.					
xv. LP15MSR5: I ask myself questions to make sure I understand the material I have been studying in this class.					
xvi. LP16MSR6: I try to change the way I study in order to fit the course requirements and the instructor's teaching style.					
xvii. LP17MSR7: I try to think through a topic and decide what I am supposed to learn from it rather than just reading it over when studying.					
xviii. LP18MSR8: When studying for this course, I try to determine which concepts I don't understand well.					
xix. LP19MSR9: When I study for this class, I set goals for myself in order to direct my activities in each study period.					
xx. LP20MSR10: If I get confused taking notes in class, I make sure I sort it out afterwards.					
d. *Effort Regulation (ER)*					
xxi. LP21ER1: I was studious while studying for this class, neither lazy nor bored.					
xxii. LP22ER2: I work hard to do well in this class even if I don't like what we are doing.					
xxiii. LP23ER3: When coursework is difficult, I don't give up and study all sections.					

Statements	SA	A	U	D	SD
xxiv. LP24ER4: Even when course materials are dull and uninteresting, I manage to keep working until I finish.					
5. Teaching Presence (TP)					
a. *T1) Design & organization*					
i. TP1DO1: The instructor clearly communicated important course topics.					
ii. TP1DO 2: The instructor clearly communicated important course goals.					
iii. TP1DO 3: The instructor provided clear instructions on how to participate in course learning activities.					
iv. TP1DO 4: The instructor clearly communicated important due dates/time frames for learning activities.					
b. *T2) Facilitation (F)*					
v. TP2F1: The instructor was helpful in identifying areas of agreement and disagreement on course topics that helped me to learn.					
vi. TP2F2: The instructor was helpful in guiding the class towards understanding course topics in a way that helped me clarify my thinking.					
vii. TP2F3: The instructor helped to keep course participants engaged and participating in productive dialogue.					
viii. TP2F4: The instructor helped keep the course participants on the task in a way that helped me to learn.					
ix. TP2F5: The instructor encouraged course participants to explore new concepts in this course.					
x. TP2F6: Instructor actions reinforced the development of a sense of community among course participants.					
c. *T3) Direct instruction (DI)*					
xi. TP3DI1: My instructor provided useful illustrations that helped make the course content more understandable to me.					
xii. TP3DI2: My instructor presented helpful examples that allowed me to better understand the content of the course.					
xiii. TP3D3: My instructor provided clarifying explanations or other feedback that allowed me to better understand the content of the course.					
6. Social Presence (SP)					
a. *SP1) Affective expression (AE)*					
i. SP1AE1: Getting to know other course participants gave me a sense of belonging in the course.					
ii. SP1AE2: I was able to form distinct impressions of some course participants.					
iii. SP1AE3: Online or web-based communication is an excellent medium for social interaction.					

Statements	SA	A	U	D	SD
b. *SP2) Open communication (OC)*					
iv. SP2OC1: I felt comfortable conversing through the online medium.					
v. SP2OC2: I felt comfortable participating in the course discussions.					
vi. SP2OC3: I felt comfortable interacting with other course participants.					
c. *SP3) Group cohesion (GC)*					
vii. SP3GC1: I felt comfortable disagreeing with other course participants while still maintaining a sense of trust.					
viii. SP3GC2: I felt that my point of view was acknowledged by other course participants.					
ix. SP3GC3: Online discussions help me to develop a sense of collaboration.					
7. Cognitive Presence (CP)					
a. *CP1) Triggering event (TE)*					
i.CP1TE1: Problems posed increased my interest in course issues.					
ii.CP1TE2: Course activities piqued my curiosity.					
iii.CP1TE3: I felt motivated to explore content-related questions.					
b. *CP2) Exploration (E)*					
iv.CP2E1: I utilized a variety of information sources to explore problems posed in this course.					
v.CP2E2: Brainstorming and finding relevant information helped me resolve content related questions.					
vi.CP2E3: Online discussions were valuable in helping me appreciate different perspectives.					
c. *CP3) Integration (I)*					
vii.CP3I1: Combining new information helped me answer questions raised in course activities.					
viii. CP3I2: Learning activities helped me construct explanations/solutions.					
ix.CP3I3: Reflection on course content and discussions helped me understand fundamental concepts in this class.					
d. *CP4) Resolution(R)*					
x.CP4R1: I can describe ways to test and apply the knowledge created in this course.					
xi.CP4R2: I have developed solutions to course problems that can be applied in practice.					

Statements	SA	A	U	D	SD
xii.CP4R3: I can apply the knowledge created in this course to my work or other non-class related activities.					

Section C: Blended MOOC Engagement model (adapted from Almutairi, 2018)
Please indicate your level of agreement in each of the following statements. The levels of agreement are:
a) strongly agree SA, b) agree A, c) undecided U, d) disagree D, and e) strongly disagree SD.

Statements	SA	A	U	D	SD
8. Campus based-course engagement (CBCE)					
a. Reflective & Integrative Learning (RIL)					
i.CBCE1RIL1: I combined ideas from different resources when completing assignments.					
ii. CBCE1RIL2: I learned things that changed my way of understanding an issue or concept					
iii. CBCE1RIL3: I connected ideas from your course to your prior experience and knowledge					
b. Higher-Order Learning (HOL)					
iv. CBCE2HOL1: I applied facts, theories, or methods to practical problems or new situations.					
v. CBCE2HOL2: I analysed ideas or theories in depth by examining their parts.					
vi. CBCE2HOL3: I formed new understanding from various pieces of information					
c. Learning Strategies (LS)					
vii. CBCE3LS1: I identified key information from reading assignments.					
viii. CBCE3LS2: I read the MOOC materials before class.					
ix. CBCE3LS3: I reviewed class notes after class.					
x. CBCE3LS4: I read the MOOC materials after class.					
xi. CBCE3LS5: I summarized what you learned in class or from course materials.					
d. Collaborative Learning (CL)					
xii. CBCE4CL1: I discussed course material to one or more students.					
xiii. CBCE4CL2: Prepared for exams or assessments by discussing or working through course material with other students.					
xiv. CBCE4CL3: I worked with other students on course projects or assignments.					
e. Student-Staff Interaction (SSI)					

Statements	SA	A	U	D	SD
xv. CBCE5SSI1: The teaching staff for this course were allow for any course-based interaction.					
xvi. CBCE5SSI2: I asked questions or contributed to course discussions in other ways.					
xvii. CBCE5SSI3: I discussed course topics, ideas, or concepts with teaching staff outside taught sessions, including by email/online.					
9. MOOC Engagement (ME)					
a. MOOC active learning (MAL)					
i. ME1MAL1: I found that MOOC materials challenged me to learn.					
ii. ME1MAL2: I used MOOC resources to improve my learning.					
iii. ME1MAL3: I used MOOC materials to make lectures more meaningful					
iv. ME1MAL4: I used MOOC quizzes to improve your understanding of a topic					
v. ME1MAL5: I shared and reflected on what I learnt in the MOOC course through blogs, micro-blogging, discussion space etc					
b. MOOC Social Interaction (MSI)					
vi. ME2MSI1: I used MOOC tools (discussion spaces, social media, and emails) to communicate with others*.					
vii. ME2MSI2: I had helpful online conversations with others.					
c. Teaching with MOOC(TWM)					
viii. ME3TWM1: The teaching staff used MOOC materials to discuss interesting issues. *					
ix. ME3TWM2: The teaching staff used campus-based and MOOCs materials in ways that improved the overall teaching.					

Section D: The Adoption and Use of Blended MOOC

Please indicate your level of agreement in each of the following statements. The levels of agreement are:

a) strongly agree SA, b) agree A, c) undecided U, d) disagree D, and e) strongly disagree SD.

Statements	SA	A	U	D	SD
10. Performance Expectancy (PE)					
i. PE1: I find the MOOC platforms useful for my studies.					
ii. PE2: Blended MOOC strategies allow me to accomplish class activities more quickly.					
iii. PE3: MOOCs enabled me to increase my productivity in learning.					
iv. PE4: The blended MOOC strategy gives me greater control over learning.					
v. PE5: Overall, I believe that the blended MOOC would enhance my effectiveness in learning.					

Statements	SA	A	U	D	SD
11. Effort Expectancy (EE)					
i. EE1: Digital learning system is convenient.					
ii. EE2: The interface of MOOCs is not simple.					
iii. EE3: Using blended MOOCs take too much time.					
iv. EE4: Learning how to use MOOC is easy.					
v. EE5: Overall, I believe that the blended MOOC is easy to use.					
12. Social Influence (SI)					
x. SI1: Most of the top Educationists think universities should use MOOCs for learning.					
xi. SI2: My Lecturers think blended MOOCs will enhance my lifelong learning so I will use them.					
xii. SI3: The strategic plan of UCC includes the use of blended MOOCs for learning.					
xiii. SI4: Students from top universities in the world are using MOOC for learning so I would do so.					
xiv. SI5: In general, the University of Cape Coast have put in place support systems for the use of blended MOOCs.					
xv. SI6: The modern education paradigm encourages learning via MOOCs as the way to teach/learn in this century.					
xvi. SI7: The University of Cape Coast is in the process of making learning in blended mode mandatory					
xvii. SI8: Government of Ghana recommends the use educational technology such as MOOC in Tertiary institutions as a means of making Ghanaians digital skilled and prepare then life in the knowledge society.					
13. Facilitating Conditions (FC)					
i. FC1: I have sufficient resources necessary to use MOOCs					
ii. FC2: I have the sufficient knowledge necessary to use MOOCs.					
iii. FC3: I know I can get support from my Lecturer /TAs and my colleagues when I face difficulties with MOOCs.					
iv. FC4: The facilities on campus in adequate for this form of instructional delivery.					
v. FC5: There are many avenues for help when I need it.					
vi. FC6: I have the resources necessary to use MOOC.					
14. Hedonic Motivation (HM)					
i. HM1: I feel fun using blended MOOC.					
ii. HM2: I enjoy using blended MOOC.					
iii. HM3: Using blended MOOC is very entertaining.					
15. Habit(H)					
i. H1: The use of blended MOOCs has become a habit for me.					
ii. H2: I am used to using blended MOOCs.					
iii. H3: I must use blended MOOCs.					

Statements	SA	A	U	D	SD
16. Task Value (TV)					
i. TV1: I think I will be able to use what I learn in this course in other courses.					
ii. TV2: It is important for me to learn the course material in this class.					
iii. TV3: I am very interested in the content area of this course.					
iv. TV4: I think the course material in this class is useful for me to learn.					
v. TV5: I like the subject matter of this course.					
vi. TV6: Understanding the subject matter of this course is very important to me.					
17. Behaviour intention to use blended MOOC (BI)					
i. BI1: I intend to complete other MOOCs immediately after this course.					
ii. BI2: I intend to use MOOCs to acquire more knowledge/skills for life.					
iii. BI3: I have resolve to use MOOCs for the remaining of my stay in UCC and after.					
iv. BI4: I will use MOOCs for lifelong learning.					
v. BI5: For my studies in UCC, I would choose blended MOOC if I were to select it among others.					
18. Actual Use of blended MOOC					
i. AU1: I have registered for other MOOCs aside from the mandated ones for UCC blended MOOCs.					
ii. AU2: I have MOOC for each of the courses enrolled at UCC.					
iii. AU3: I have used blended MOOC after the initial introduction during my academic period.					
iv. AU4: I use many functions of blended MOOC (e.g., discussion forum, chat session, messaging, downloading course contents, uploading assignments, etc.)					

Section E: Satisfaction and Academic Performance in using blended MOOC.
Please indicate your level of agreement in each of the following statements. The levels of agreement are:
a) strongly agree SA, b) agree A, c) undecided U, d) disagree D, and e) strongly disagree SD.

Statements	SA	A	U	D	SD
19. Student Satisfaction (SS)					
i. SS1: I find the MOOC platforms useful for my studies.					
ii. SS2: This course contributed to my educational development.					
iii. SS3: This course contributed to my academic development.					
iv. SS4: I am satisfied with the level of interaction that happened in this course.					
v. SS5: In the future, I would be willing to take a fully online course again.					
vi. SS6: Overall, I am satisfied with this class.					

20. Academic Performance (AP)					
i. AP1: I believe I will receive an excellent grade in this class.					
ii. AP2: I'm confident I did an excellent job on the assignments and tests in this course.					
iii. AP3: I expect to do well in this class.					
iv. AP4: I'm certain I have mastered the skills being taught in this class.					
v. AP5: Considering the difficulty of this course, the teacher, and my skills, I think I will do well in this class.					

THANK YOU