

Exploring the Use of Customised Generative AI in First-Year Accounting Learning: A Case Study of a Private Higher Education Institution (PHEI)

Student Number: 201505722

Student Name: Evendree Reddy

Supervisor: Professor S. Reddy

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Declaration:

Submitted in fulfilment of the academic requirements for the degree of **Master of Education in Higher Education**, in the graduate programme within the School of Education, College of Humanities, University of KwaZulu-Natal, Edgewood, South Africa.

I, Evendree Reddy, declare that:

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Evendree Reddy

Student Name

15 January 2026

Date

Professor S. Reddy

Name of Supervisor

Dedication

I dedicate this achievement to the King of Kings and the Lord of Lords, Jesus Christ. I have reached this milestone only by His grace! There were days when I felt my lowest, overwhelmed and exhausted. But each time, reminded by His promises, I grew strength to face another chapter and to persevere on..... "I can do all things through Christ who strengthens me" Philippians 4:13.

The Lord is my shepherd, I lack nothing.
He makes me lie down in green pastures,
He leads me beside quiet waters,
He refreshes my soul.
He guides me along the right paths
for His name's sake.
Even though I walk
through the darkest valley,
I will fear no evil,
for you are with me;
your rod and your staff,
they comfort me.

You prepare a table before me
in the presence of my enemies.
You anoint my head with oil;
my cup overflows.
Surely your goodness and mercy will follow me
all the days of my life,
and I will dwell in the house of the Lord
forever.

Psalm 23

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Abstract

This study explores the integration of a customised Generative AI tool in a first-year Accounting module at a Private Higher Education Institution (PHEI) in South Africa, addressing the empirical gap regarding AI's conditional effectiveness in professional education contexts.

Using an explanatory sequential mixed-methods design, quantitative survey data from 149 students was followed by qualitative semi-structured interviews and focus groups with 24 students. The central finding is that student responses were predominantly neutral across multiple constructs (40–47%), reflecting accurate learner assessment of context-dependent, rather than universally positive or negative AI effectiveness. AI supported foundational declarative knowledge acquisition and initial concept learning but proved insufficient for procedural competence development and higher-order assessment preparation, revealing a persistent theory-practice gap. A strong positive correlation between Ease of Use and Perceived Usefulness ($p = 0.692$, $p < 0.01$) identified usability as a pedagogical gatekeeper, with usability barriers preventing engagement regardless of content quality.

Theoretically, findings extend the Technology Acceptance Model into an Educational context (ETAM-E), refine Self-Directed Learning theory for professional education settings, and synthesise these extensions into an Integrated Conditional Effectiveness Framework for AI-Enhanced Learning (ICEFL). Together, these contributions advance understanding of the conditions under which AI supports learning in South African higher education. The study advocates for strategic, evidence-based, and pedagogically intentional AI implementation rather than uncritical technology adoption.

Abbreviations

4IR	Fourth Industrial Revolution
5IR	Fifth Industrial Revolution
ACC1A	Accounting 1A (module code)
APP	Application
HCMUTE	Ho Chi Minh City of Technology and Education
HEI	Higher Education Institution
IoT	Internet of Things
LLM	Large Language Model
PEOU	Perceived Ease of Use
PoC	Proof of Concept
PU	Perceived Usefulness
PwC	PricewaterhouseCoopers
SAHEIs	South African Higher Education Institutions
SDL	Self-directed Learning
STARA	Smart Technology, Artificial Intelligence, Robotics and Algorithms
TAM	Technology Acceptance Model
TVET	Technical and Vocational Education and Training

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Chapter 1: Generative Artificial Intelligence in Accounting Learning

1.1 Introduction

This chapter presents the background and context for the study, which constitutes a case study exploring students' learning experiences of a customised Generative Artificial Intelligence (AI) tool in a first-year Accounting module at a private higher education institution (PHEI). An introduction to the learning challenges students face in higher education in South Africa, the teaching and learning challenges encountered in Accounting education, the role of Generative Artificial Intelligence in addressing these challenges, and the considerations for AI's integration into Accounting education in South Africa establishes the foundation for understanding the study's significance and contribution.

The chapter proceeds by first contextualising the study within South African higher education challenges (Section 1.2), then establishing the study's significance and beneficiaries (Section 1.3), articulating the problem statement (Section 1.4), addressing researcher positionality (Section 1.5), stating research objectives and questions (Section 1.6), defining key terms (Section 1.7), previewing the dissertation structure (Section 1.8), and concluding with chapter synthesis (Section 1.9).

1.2 Background and Context

1.2.1 Elucidating Generative AI's Positioning Within the South African Higher Education Landscape

Students at South African Higher Education Institutions (SAHEIs) experience unique learning challenges owing to the country's legacy of Apartheid and systemic unequal schooling system (Maree, 2015). Differences in students' academic preparedness, large classes, challenges with English as the medium of teaching and learning, and inadequate curriculum design all contribute to the learning challenges students face within South African higher education (Funda & Piderit, 2024). An alarming statistic reveals that South Africa has one of the world's highest dropout rates, with 50% to 60% of first-year students discontinuing their studies (Mlambo & Mpanza, 2024). Among the modules with high dropout rates is Accounting. First-year Accounting students in South African universities face persistent challenges in mastering foundational concepts, contributing to high dropout rates, extended time-to-degree completion, and limited employability (Makhathini et al., 2024). A deeper

understanding is therefore required pertaining to the interaction between the student, university, and the greater higher education context to ensure a teaching and learning environment within higher education that positions students for success (Mashile et al., 2020).

Maree (2015) extends a call to action for the implementation of teaching and learning strategies that promote cooperative learning, self-directed study, contextualised learning using real-world examples, eclectic approaches, active learning, and student motivation to address the learning challenges students experience in higher education. Emerging literature suggests Generative AI may offer opportunities to address some challenges in South African higher education, particularly through supporting active learning approaches (De Villiers-Botha, 2024). AI-driven learning systems, with their ability to offer personalised feedback and adaptive learning pathways, have the potential to alleviate cognitive barriers and improve students' grasp of complex module concepts, such as Accounting (Patel & Ragolane, 2024). However, AI integration in education remains contested, with scholars raising concerns about academic integrity, critical thinking development, and equity of access (Selwyn, 2019; Watanabe, 2024). Evidence regarding AI's effectiveness remains limited, particularly in South African contexts, warranting empirical investigation.

A survey of five South African Higher Education Institutions' (HEIs) undergraduate students across different faculties revealed that students are using various AI tools such as ChatGPT, Grammarly, Quillbot, and Mendeley (Bosch et al., 2023). The survey further revealed that students use these AI tools for diverse purposes including clarifying concepts, structuring assignments, improving writing, and exam preparation (Bosch et al., 2023). The integration of ChatGPT is another tool that is encouraged in Accounting classrooms to augment learning, offer multi-lingual support, develop students' critical thinking skills, and to create personalised learning experiences for students (Burney et al., 2023).

It is against this backdrop that this research presents a case study at Emeritus College¹, which involves an exploration into the role of Generative AI in shaping first-year Accounting students' learning at a private tertiary institution in South Africa. The

¹ To maintain the anonymity and confidentiality of the institution within which this study is located, a pseudonym has been used. Gatekeeper permission was received from the institution permitting the use of the pseudonym.

study specifically investigates how AI-driven interventions can facilitate cognitive engagement, support self-directed learning, and enhance conceptual mastery in Accounting. Moreover, the case study examines the potential challenges in AI-mediated learning environments (Selwyn, 2019). This research study therefore provides empirical insights into the benefits and limitations of AI in shaping students' learning outcomes for South African first-year Accounting students, contributing to the broader discourse on digital transformation in higher education.

1.2.2 Considerations for AI's Integration in Accounting Education

A key consideration for the effective integration of AI in higher education is the acknowledgement of the challenges highlighted in literature. One of the main challenges relates to the ethical use of AI, including data privacy and security (Xia et al., 2024). Whilst the SA AI Policy Framework advocates for existing data protection regulations to be strengthened, privacy, pertaining to issues such as data leakage and misuse, remains a sensitive topic within the discourse of AI use in higher education institutions (Xue et al., 2025).

Limited interaction, misleading and outdated responses, insufficient personalised feedback, and difficulty in adapting to technology constitute some of the challenges encountered by students (Gokceaslan et al., 2024). For lecturers, challenges range from dealing with increased student plagiarism, under-preparedness of students to use AI, and the complex nature of incorporating AI into effective teaching and learning (Gokceaslan et al., 2024). Inconsistencies, hallucinations, and biases are further limitations identified, requiring students to be critical and cautious about the information generated by AI (Swindell et al., 2024). Researchers like Watanabe (2024) also critique AI for hindering students' ability to think critically and independently.

Thus, whilst the technology of AI is exciting and holds potential benefits for Accounting education, the associated challenges, which include pedagogical implications as highlighted by Castello-Sirvent et al. (2024), must be understood at a deeper level. This provides justification for the case study, which presents both the benefits and challenges for AI's ethical incorporation into teaching and learning practice within a first-year Accounting module at Emeritus College. In addition to understanding the benefits and challenges of incorporating AI into teaching and learning strategies, it remains imperative for higher education institutions to also consider effective policies

and guidelines for students' use of AI, aligning to faculty goals and learning outcomes, whilst maintaining access and privacy of students' data (Moore & Lookadoo, 2024). A holistic consideration of all factors that impact on AI's effective integration is critical for understanding the factors that will aid meaningful learning in a module like Accounting, support institutional effectiveness, and promote sustainability of AI integration into pedagogy.

In summary, through a review of the aforementioned considerations, this study is positioned to contribute empirically to the discourse on Generative AI's integration within South African higher education by specifically addressing the gap in knowledge pertaining to students' learning experiences of AI-generated resources in first year Accounting education. This understanding presents insights towards effective and contextually sensitive AI adoption in higher education, cognisant of the benefits and challenges inherent to integrating AI into curriculum design in higher education.

1.3 Significance of the Study

1.3.1 Justification

This study addresses a significant gap in South African higher education research by providing empirical evidence on student experiences with AI-integrated learning in Accounting education. While international literature documents AI adoption in various educational contexts, limited research examines AI effectiveness in South African higher education institutions, particularly in foundational Accounting courses where students face substantial conceptual challenges. The study's significance lies in its systematic investigation of both benefits and limitations through mixed-methods inquiry, moving beyond enthusiasm or scepticism toward evidence-based understanding of AI's conditional effectiveness in professional education contexts.

The research contributes theoretically by applying and extending Self-Directed Learning theory and Technology Acceptance Model in AI-enhanced educational contexts, examining how technology mediates learner autonomy and shapes adoption patterns. Methodologically, the study demonstrates rigorous mixed-methods design integrating quantitative patterns with qualitative explanations, providing a model for investigating educational technology effectiveness. Practically, findings inform pedagogical design principles, institutional policies, and curriculum development strategies for AI integration not only at Emeritus College but potentially across South

African higher education institutions facing similar challenges of high dropout rates, large classes, and diverse student preparedness levels.

1.3.2 Beneficiaries

This case study contributes to the ongoing discourse on educational innovation and the benefits and challenges of AI adoption in South African higher education to address learning challenges in Accounting education. The beneficiaries therefore include multiple stakeholders within higher education, including students and lecturers at Emeritus College and other institutions, instructional designers, and policymakers.

De Villiers and Farrington (2017) recommend providing students with opportunities to identify and summarise unfamiliar Accounting terminology and to complete online self-assessments to support the mastery of learning outcomes and address learning challenges in Accounting education. ACC1A students at Emeritus College may benefit from the outcomes if findings inform improved AI integration in future course iterations. The case study centres around this exact opportunity, examining ACC1A students' learning experiences and perceptions of engaging with AI-generated lecture summaries and pathway questions. This understanding of their engagement and perceptions, specifically how AI-generated resources shaped their learning experience, will inform future iterations of AI-supported learning in Accounting education at Emeritus College, guiding student-centred teaching and learning. The outcomes are expected to inform the development of more effective AI integration in first-year Accounting modules, potentially enhancing students' engagement with learning content and academic outcomes at Emeritus College. By evaluating the exact characteristics of Generative AI's potential to enhance students' learning outcomes and skills development, the research presents insights into educational innovation to guide its adoption more broadly within South African higher education (Santos & Serpa, 2023).

In addition to students, Accounting lecturers also stand to gain value from this study. Within the South African higher education context, lecturers face challenges such as large class sizes, diverse student backgrounds, and varied learning needs, making it difficult to provide individualised support (Patel & Ragolane, 2024). The outcomes of this case study present an understanding of how the use of a customised Generative AI tool in this context shapes students' self-directed learning in a first-year Accounting

module, providing lecturers with insights on how to effectively incorporate AI into their teaching practice to facilitate deeper comprehension of concepts and enhance students' self-efficacy (Wu et al., 2024). Lecturers will gain insights to engage with AI tools for improved teaching and learning, thereby enhancing educators' preparedness to effectively utilise AI tools in Accounting education (Celik, 2023, cited in Bobula, 2024). According to Advani (2023), for higher education in South Africa to prepare its students for the Fourth Industrial Revolution (4IR), lecturers need to act as facilitators and enablers such that the responsibility for the development of skills rests with the students (Singaram et al., 2023).

The findings of the case study contribute to the discourse on AI's pedagogical value and inform best practices for the practical integration of AI into curriculum design for application at Emeritus College and more broadly in higher education, benefiting both instructional and curriculum designers. These insights are critical for strategic curriculum design, ensuring that the curriculum prepares Accounting students for 4IR (Muzuva, 2024). Moreover, understanding the impact of AI-generated resources on students' learning strategies, development of critical thinking, and problem-solving informs curriculum and instructional designers on how to embed AI to scaffold students' learning within educational frameworks.

Lastly, the outcomes of the case study provide evidence-based insights for policymakers in higher education. The insights gained from the study will serve to inform policymakers on revisions to the current Teaching and Learning Strategy, specifically related to the use of technology in teaching and learning and promotion of diversity, which are the two constructivist concepts that constitute the foundation of the teaching and learning approach at Emeritus College (The IIE, 2025). According to Moore and Lookadoo (2024), policy frameworks, such as the Teaching and Learning Strategy at Emeritus College, are critical in that transparent guidelines reduce confusion, promote equitable access, and shift the focus from performance to meaningful learning. According to Patel and Ragolane (2024), acceptance by policymakers can lead to increased student engagement and support the ethical use of AI.

1.4 Problem Statement: Teaching and Learning Challenges in First-Year Accounting

South African higher education institutions are characterised as having high access but low throughput rates (Manik, 2015). This is because the access impetus in higher education has been given priority as a means of redress for historically marginalised groups, with limited focus on strategies to support the success of its students (Department of Higher Education & Training, 2024; Mashile et al., 2020; Manik, 2015). Private HEIs also struggle to strike the balance between business and academic imperatives (Stander & Herman, 2017). Ultimately, this reality culminates in students who struggle with English as the medium for teaching and learning, lack competence in study management, demonstrate inadequacies in coping skills, and lack self-directed study skills within unsupportive learning environments (Steyn & Kamper, 2011; Maree, 2015).

Whilst these struggles students encounter are prevalent across various modules, the problem at the heart of this study is the learning challenges encountered by students in first-year Accounting modules. Calma (2020) asserts that the intensity of Accounting coursework is overwhelming for students and requires self-directed study and preparation (Baard et al., 2025). The underdevelopment of such skills, including numeracy skills at secondary level, and problems related to conceptualisation are some of the main contributing factors to the learning challenges students encounter in first-year Accounting modules (Baard et al., 2025; Olifant et al., 2024). This has a domino effect, contributing to high dropout rates, extended graduation timelines, and limited employability which characterise Accounting degrees (Makhathini et al., 2024). Given the role of Accounting as a scarce and essential skill in the country, the quality of Accounting education and the concomitant understanding of students' learning experiences and academic performance is vital to the country's economic and social development (Parker & Van Rooyen, 2024).

Students' learning challenges pertaining to inquiry, critical thinking, and logical analysis necessary for success in Accounting modules raise concerns about the effectiveness of current teaching and learning methods employed within Accounting to equip students with the required competencies for academic progression and workforce readiness (Makhathini et al., 2024). It is argued that traditional teaching and learning approaches may not fully address students' diverse learning needs, particularly in the transition to higher education, and lack the practical application to

relate concepts to real-life scenarios (Patel & Ragolane, 2024; Olifant et al., 2024). A traditional approach to teaching is characterised as being passive and predominantly based on the ability to remember facts versus active teaching which requires students to be active participants in the learning process, where, for example, such an approach could include the use of a case study that requires students to think and analyse information (Stejskalová et al., 2019). Olifant et al. (2024) advocate for an active teaching and learning approach in Accounting which encourages classroom interaction and greater comprehension of concepts.

Owing to the growing integration of technology in education, according to literature, Generative AI presents a potential solution to support active teaching and learning, improving student engagement and the effective comprehension of concepts, thereby addressing the problems identified within Accounting education (Hazari, 2024). However, its impact on students' achieving their learning outcomes remains largely unexplored, providing justification for this study situated within a first-year Accounting module (Khoalenyane & Ajani, 2024). Moreover, in a study by De Villiers and Farrington (2017) motivated by the poor pass rates in Accounting, particularly at first-year level, the authors recommend providing students with opportunities to identify and summarise unfamiliar Accounting terminology and to complete online self-assessments to support mastery of learning outcomes. This provides direct justification for this case study, which constitutes an exploration into how AI-generated lecture summaries and pathway questions shape students' learning in a first-year Accounting module (ACC1A) that covers the foundational understanding of contemporary Accounting terminology, concepts, and principles at Emeritus College.

1.5 Positionality

1.5.1 Power Dynamics

Positionality of a researcher is described as the researcher's perceptions, values, and beliefs which have an influence on the researcher's study in terms of the process, outcomes, and results (Darwin Holmes, 2020). It is therefore important for a researcher to develop an acute self-awareness of one's positionality such that it does not lead to bias in the research process. A further aspect to positionality that remains an important aspect for consideration to mitigate risk in a research study is power dynamics. In settings where the researcher holds a particular rank, social status, or

privilege, achieving equitable power between the researcher and the population being researched requires careful and sensitive navigation (Andress et al., 2020).

For an equitable power dynamic to be achieved in research, it is critical that the researcher acknowledges his or her rank, social status, or privilege and is transparent about this with the population being researched. It is also important for participants in a research study to be given an opportunity to question the role of the researcher and the objectives of the research, such that participants see themselves as co-creators of the research study through their participation (Andress et al., 2020). Adopting the co-creation approach establishes the power balance in the relationship between the researcher and the participant, ensuring buy-in and collective ownership of the research to create new knowledge (McDonald, 2020).

It must be noted, however, that power must be seen on a continuum and therefore a level of flexibility needs to be maintained throughout the process of research, which is also a fluid and dynamic process. According to Kaaristo (2022), being emotionally astute in utilising interpersonal skills to navigate the power-play is critical. The author therefore encourages the use of humour as a technique to diffuse any tensions that may arise in the researcher-participant relationship (Kaaristo, 2022). Maintaining balance of power between the researcher and participants is therefore possible but requires the researcher to take strategic decisions to achieve this end, which ultimately also support the research process, outcomes, and results.

1.5.2 Outsider-Insider Lens

The researcher's awareness of their position as an outsider and insider remains central to the research process (Bukumal, 2022). As an insider, the researcher is seen to share certain attributes with the participants or holds a certain level of knowledge of the research context by virtue of the researcher's professional status and experience in that context (Bukumal, 2022) and presents ease of access to the research site (Muasya, 2023). By converse, this definition suggests that the researcher's position as an outsider translates into a lack of shared attributes between the researcher and the participants or the lack of knowledge into the research context.

Both positions have their benefits and limitations. Chhabra (2020) therefore suggests that the researcher assume an in-between position to align with the dynamic nature of research, enabling the researcher to be both objective, yet sensitive to the context and

the participants at the same time. This sentiment of not viewing positionality from a binary perspective (that is, either an insider or outsider) but from an in-between status is supported by Dwyer and Buckle (2009), indicating that the binary is restrictive and does not allow the researcher to appreciate the fluidity of the research process and the complexity of human experience.

The key benefit of adopting an in-between positionality according to Komalasari et al. (2022) is that it enables a level of flexibility and a deeper understanding of the participants' experiences. This is achieved by the researcher acquiring a greater comprehension of the phenomenon being studied through an appreciation of the different perspectives attributable to the in-between positionality lens (Liu & Burnett, 2022). Greater respect and shared learning enabled through this positionality also results in a more collaborative research process (Liu & Burnett, 2022). In summary, assuming an in-between status serves to diffuse the power struggle, and enables shared trust and collaboration between the researcher and participants (Mullings, 1999).

1.5.3 Reflexivity

Reflexivity is the process by which a researcher takes an active role to critically reflect on one's positionality throughout the research process, considering perspectives, power, and status for valuable meaning-making in the research process (Bukumal, 2022). Brown (2023) suggests the use of a reflective journal and a list of reflective questions to support this reflexive process, enabling the researcher to make objective decisions through the research process. Along with objective decision-making, the reflexive process also enables acknowledgment of the researcher's influence, such that the comparison and combination of both the researcher's and the participant's knowledge and experiences create new knowledge (Ide & Beddoe, 2024).

Embedding reflexivity across qualitative and quantitative research methods is therefore necessary, particularly in mixed-methods studies, adding to the credibility and rigour of the study (Jamieson et al., 2023). Applying reflexivity across all aspects of the study's design, making deliberate decisions to guide the collaboration between the researcher and participants, exploring different types of reflexivity, and establishing a balance between the researcher's objective and subjective perspectives improves the quality of the research design, process, and outcomes (Olmos-Vega et al., 2023).

1.5.4 Position Statement

My positionality in this study has been complex as I have had to consider my dual role as an insider and an outsider; however, I have taken strategic decisions to enhance the quality and rigour of this study. I have had to carefully consider my rank as the Head of Campus at Emeritus College and the power dynamic based on my institutional knowledge and access which positions me as an insider (Andress et al., 2020; Bukumal, 2022; Muasya, 2023). Simultaneously, I have acknowledged my position as an outsider due to the lack of my direct engagement with students and their learning experiences, as I am not a lecturer.

By virtue of the duality of my position in this study, I adopted an in-between status that enabled me to be objective, yet sensitive to the context and the student participants (Chhabra, 2020; Dwyer & Buckle, 2009). Through the co-creation of knowledge, I have mitigated imbalances and maintained transparency with the participants (McDonald, 2020). By valuing and inviting the students' input pertaining to their experiences of engaging with a customised Generative AI tool in their first-year Accounting module, and maintaining collaborative engagement, this fostered an equitable researcher-participant relationship (Andress et al., 2020).

Guided by literature and the use of a reflective journal and questions, I have applied reflexivity and have been able to critically examine my assumptions, position, and influence on the study's design, process, and outcomes (Bukumal, 2022; Brown, 2023). Embedding reflexivity across all aspects of the study's design, as well as its incorporation into the mixed-method study approach has added credibility and rigour to the study (Olmos-Vega et al., 2023; Jamieson et al., 2023) and the collaborative creation of new knowledge (Ide & Beddoe, 2024).

1.6 Objectives of the Study and Its Critical Research Questions

This case study is framed within the broader South African higher education context and the unique learning challenges students experience, particularly at first-year Accounting level. Acknowledging the emerging body of literature which positions the incorporation of Generative AI in higher education as potentially beneficial to addressing learning challenges, this research focuses on how students utilise a customised Generative AI tool to engage with AI-generated lecture summaries and pathway questions, providing insights into the role of AI in shaping student learning experiences, fostering critical skills, and supporting mastery of learning outcomes. The

case study therefore presents the learning experiences of the students enrolled in the ACC1A module.

The conceptualisation of the objectives and critical research questions commenced with a systematic literature review to enhance knowledge related to the South African higher education context and the learning challenges in Accounting education, and the current trends and gaps in research pertaining to the use of Generative AI to address these challenges (Farrugia et al., 2010). This, in appreciation of the understanding that the research questions ultimately guide the research study. Clearly defined research objectives create structure for the intended outcomes of the study and relevant research questions support the achievement of the study's intended outcomes (Farrugia et al., 2010).

The purpose and objectives of this study are threefold:

- a. to explore first-year students' experiences of engaging with AI-generated lecture summaries and pathway questions in their learning process of the ACC1A module.
- b. to examine how the customised Generative AI tool shapes first-year students' understanding of learning outcomes and skill development in the ACC1A module.
- c. to investigate why first-year students perceive AI-generated resources as beneficial or challenging in supporting their learning in the ACC1A module.

The central research question that frames this study is: How does a customised Generative AI tool shape students' learning experiences in the ACC1A module?

This central question is addressed through three research sub-questions:

RQ1: What are first-year students' learning experiences of engaging with AI-generated lecture summaries and pathway questions in the ACC1A module?

RQ2: How does the customised Generative AI tool shape first-year students' understanding of learning outcomes and skill development in the ACC1A module?

RQ3: Why do first-year students perceive AI-generated resources as beneficial or challenging in supporting their learning in the ACC1A module?

1.7 Conceptualisation of Key Terms

In this section, the key terms referred to in literature are defined:

1.7.1 Customised Generative AI Tool

A customised Generative AI tool is a Large Language Model (LLM) adapted to perform specialised tasks, such as enhancing engagement and providing personalised learning experiences in higher education (Garrido-Merchan, 2024). An example of a customised Generative AI tool within the South African higher education context is the AE BOT developed at the University of Pretoria. The AE BOT incorporates AI to improve student prompts, with theory-based prompts and curriculum-aligned content, providing a personalised and context-driven learning assistant to support students' learning of Accounting (Coetzee, 2024). According to Khoalenyane and Ajani (2024), customising Generative AI for specific educational contexts accelerates its adoption and integration into pedagogical practices through personalised feedback, automated assessment, and adaptive learning.

1.7.2 ReX and Merlin

ReX and Merlin are customised Generative AI tools created to assist Emeritus College with evidence-based instruction and content creation in the form of lecture summaries and pathway questions (Garrido-Merchan, 2024). ReX is the database that contains learning objectives, course materials, and content references (Stefan, 2023). ReX uses a human-in-the-loop approach, incorporating human intervention in the form of module leaders to establish the ReX database and fulfill specific course requirements, facilitating the creation of pedagogically sound content to achieve the Proof of Concept's (PoC) contextual goals (Memarian & Doleck, 2024). On this basis, it is referred to as a customised Generative AI tool.

Students' learning and engagement are supported and scaffolded by the instructional tool MERLIN (Neo, 2021). MERLIN is the interface that compares lecture recordings against the ReX database, analysing and converting the content into useful and interactive materials like pathway questions and lecture summaries to be used by the students (Vasquez-Parra et al., 2024). ReX and Merlin are therefore interdependent. The pathway questions and lecture summaries, aimed at supporting effective teaching and learning, are available to students on the MathU platform, which is a mobile application that students access via their cellphones (MathU, 2025).

1.7.3 Proof of Concept (PoC)

A Proof of Concept is a preliminary implementation used to test the feasibility and effectiveness of a model before full-scale deployment (UK Department of Education,

2024). ReX and MERLIN (i.e., Generative AI) are implemented at Emeritus College as a PoC within selected modules to support evidence-based teaching and evaluate its effectiveness in enhancing teaching and learning, its usability, and potential for broader application. Evidence-based teaching can be defined as teaching that is informed by empirical evidence which serves as a resource for corrective action or strategic teaching guide, supporting the lecturer to make intentional decisions for effective teaching and learning (Diery et al., 2020). The contextual goal of the PoC is to evaluate the potential of the customised Generative AI tool to provide lecturers with empirical evidence for this purpose. However, the purpose of this proposed study seeks to explore the learning experiences of students within the PoC, specifically the ACC1A module.

1.7.4 AI-Generated Resources (Summaries and Pathway Questions)

AI-generated resources refer to lecture summaries and pathway questions (known to students as homework questions) which are generated by MERLIN from lectures recorded in real-time (MathU, 2025). Pathway questions follow a branching format supporting interactive learning, enabling students to navigate interconnected questions (i.e., main questions followed by sub-questions), which guide them towards the correct understanding (D2L, 2024). This approach reinforces learning and provides personalised support, further aided by reports that track student progress for targeted support (MathU, 2025). According to Wu et al. (2024), this reveals AI's potential to shape students' self-directed learning by strengthening students' digital literacy through the use of AI-generated resources, supporting lecturers to incorporate AI into their teaching practice, facilitating deeper comprehension of concepts, and enhancing students' self-efficacy.

1.8 Overview of Dissertation

This dissertation comprises seven chapters progressing from contextualisation through methodology to findings, discussion, and conclusions.

Chapter 1 provides a comprehensive introduction, establishing the study's context within South African higher education challenges and articulates the problem statement regarding first-year Accounting students' learning difficulties. The chapter presents the researcher positionality, research objectives and questions (RQ1, RQ2, RQ3) and the definition of key terminology referred to within the study.

Chapter 2 presents a systematic literature review examining AI in higher education generally and accounting education specifically, identifying empirical and theoretical gaps justifying this study. It further establishes the theoretical lenses of Self-Directed Learning theory, Technology Acceptance Model, and constructivism, and identifies the gaps in current knowledge that this study addresses.

Chapter 3 details the research methodology employed in the study, describing the explanatory sequential mixed-methods design employed, commencing with a quantitative survey, followed by semi-structured interviews and focus groups (Creswell & Plano Clark, 2018). Chapter 3 outlines the sampling strategy, data collection instruments, outlines the analytical approaches, addresses the ethical considerations and quality criteria.

Chapter 4 presents quantitative findings from survey data analysing 149 first-year Accounting students' perceptions of the AI tool's usefulness, ease of use and contribution to their learning. Findings are interpreted through TAM and SDL frameworks, with a critical reflection of the limitations. The chapter demonstrates appropriate statistical analysis with transparency about what can and cannot be claimed from the data.

Chapter 5 presents the qualitative findings from semi-structured interviews and focus group discussions, providing rich narrative accounts that illuminate the mechanisms underlying quantitative patterns identified in Chapter 4.

Chapter 6 discusses findings through theoretical and empirical lenses, articulating contributions and extensions to scholarship and implications for practice, policy, and future research.

Chapter 7 concludes the dissertation by synthesising overall contributions in relation to the research questions, presenting recommendations for Accounting education practice and policy, suggesting directions for future research, and offering a final reflection on the research journey.

1.9 Conclusion

This chapter presented a comprehensive overview of the background and context which frames this case study of a customised Generative Artificial Intelligence (AI) tool in a first-year Accounting module at a private higher education institution, exploring

students' learning experiences. This included an introduction to the learning challenges students face in higher education in South Africa, the teaching and learning challenges encountered in Accounting education, emerging literature positioning Generative AI as potentially addressing some of these challenges while acknowledging contested debates about AI in education, and the considerations for AI's integration into Accounting education in South Africa, presenting justification for the case study.

The significance of the study was established through identification of empirical gaps in South African higher education research and articulation of multiple beneficiaries including students, lecturers, instructional designers, and policymakers. The problem statement powerfully articulated the specific challenges facing first-year Accounting students within broader South African higher education contexts characterised by high access but low throughput, diverse student preparedness, and inadequate support systems. Positionality was outlined comprehensively, addressing power dynamics, insider-outsider tensions, and reflexivity to convey commitment to a robust and rigorous study conducted with transparency and ethical sensitivity.

The objectives and three research questions (RQ1, RQ2, RQ3) illustrated the purpose of the study, exploring students' learning experiences with AI-generated resources (RQ1), examining how AI shaped understanding of learning outcomes and skill development (RQ2), and investigating why students perceived benefits or challenges (RQ3). Key terms were defined to ensure conceptual clarity, including customised Generative AI tools, the ReX and Merlin system, Proof of Concept implementation, and AI-generated resources. Finally, an overview presented the structure of the dissertation across seven chapters, demonstrating logical progression from introduction through literature review and theoretical framework, methodology, quantitative and qualitative findings, discussion, to conclusion.

Chapter 2 progresses to the literature review, providing a comprehensive examination of empirical scholarship on AI in higher education and accounting education specifically, while establishing the theoretical framework, Self-Directed Learning theory and Technology Acceptance Model, that grounds the investigation and guides analysis throughout the study.

Chapter 2: Literature Review

2.1 Introduction

This chapter presents a systematic literature review establishing the theoretical and empirical foundation for the study. The review synthesises existing scholarship on Generative AI's integration into higher education, identifies gaps in current knowledge, and articulates the study's contribution to ongoing discourse regarding AI in education. A critical analysis of literature enables the study to be situated within broader debates about AI adoption benefits and challenges, illuminating gaps that justify this investigation (Abdallah, 2024; Snyder, 2019).

The chapter progresses systematically through interconnected themes. Section 2.2 establishes the theoretical framework integrating Self-Directed Learning theory, Technology Acceptance Model, and constructivist principles that ground the investigation and guide analysis throughout. Section 2.3 contextualizes AI within Fourth Industrial Revolution imperatives and their implications for higher education transformation. Section 2.4 examines AI technologies, particularly Large Language Models and chatbots, providing technical background for understanding the customised Generative AI tool under investigation. Section 2.5 reviews empirical evidence on student engagement with AI and documented benefits across diverse educational contexts. Section 2.6 identifies challenges and barriers to effective AI adoption, particularly within South African higher education contexts. Section 2.7 examines Generative AI specifically within Accounting education, connecting technological possibilities to disciplinary pedagogical challenges. Section 2.8 concludes by synthesising themes and transitioning to the methodology chapter.

2.2 Theoretical Framework

The theoretical framework for this study integrates Self-Directed Learning (SDL) theory and Technology Acceptance Model (TAM) as primary analytical frameworks, with constructivist principles providing the overarching pedagogical lens through which these frameworks operate. This multi-theoretical approach enables comprehensive analysis of student engagement with AI-generated resources, examining adoption patterns (TAM), learning process dynamics (SDL), and pedagogical appropriateness (constructivism).

SDL theory posits that effective learners exhibit self-management (planning and executing learning activities), self-monitoring (evaluating progress and identifying gaps), and intrinsic motivation (internal drive to learn) (Garrison, 1997; Knowles, 1975). TAM explains technology adoption through two primary constructs, perceived usefulness (the degree to which technology enhances performance on valued tasks) and perceived ease of use (the degree to which technology requires minimal cognitive effort) (Davis, 1989). Constructivism emphasises that meaningful learning occurs through active knowledge construction via learner-directed exploration, social interaction, and authentic problem-solving, rather than passive information transmission (Vygotsky, 1978; Bransford et al., 2000).

These frameworks enable multidimensional interpretation of study findings. SDL theory helps explain why students perceive certain AI features as valuable (those supporting autonomous learning) while TAM explains how usability concerns moderate these perceptions. Constructivism provides pedagogical criteria for evaluating whether AI implementation supports authentic learning or merely information delivery. Together, the frameworks illuminate when, why, and for whom AI enhances or constrains learning in professional education contexts.

Additionally, Bloom's Taxonomy (1956) serves as an analytical tool for classifying cognitive levels addressed by AI-generated resources. The taxonomy's six levels, remembering, understanding, applying, analysing, evaluating, and creating, enable systematic assessment of whether AI supports only lower-order thinking skills or scaffolds progression toward higher-order cognitive competencies required for professional Accounting practice. This analytical lens complements theoretical frameworks by providing structured vocabulary for discussing cognitive development.

The following subsections elaborate each framework's specific theoretical propositions and application to this study's investigation.

2.2.1 Self-Directed Learning Theory (SDL)

SDL represents the study's primary theoretical framework examining learner autonomy. Knowles (1975) conceptualised SDL as a process whereby learners take initiative, with or without assistance, in diagnosing learning needs, formulating goals, identifying resources, choosing strategies, and evaluating outcomes. Garrison (1997) refined this conceptualisation by identifying three interdependent dimensions, self-

management (task control and planning), self-monitoring (cognitive responsibility including metacognitive awareness), and motivation (entering and persisting in learning).

Morris (2024) extends SDL theory by proposing four dimensions, control of the learning process (management of learning tasks), characteristics of the learner (preference, skill, and intrinsic motivation), contextual factors (social constraints, educator characteristics, and environmental conditions), and responsibility (self-regulation and accountability). This expanded framework recognises that SDL operates within situated contexts where institutional structures, assessment demands, and resource availability shape learners' capacity for autonomous learning.

In technology-enhanced learning contexts, SDL theory predicts that tools supporting learner autonomy, providing flexible access to resources, and facilitating accurate self-assessment will enhance learning outcomes and be perceived as valuable by students. Conversely, technologies constraining autonomy, imposing rigid structures, or providing inaccurate feedback will undermine SDL development regardless of content quality.

Through the SDL lens, this study evaluates students' readiness against three dimensions, intrinsic motivation (inherent satisfaction in learning beyond external rewards), self-management skills (ability to independently engage in autonomous learning activities), and self-monitoring competencies (capacity to accurately judge when AI-generated resources match learning needs and when alternative resources are more appropriate). Simultaneously, the AI tool is evaluated for its efficacy in supporting or constraining SDL dimensions. For example, on-demand access to summaries may support self-management by enabling flexible study scheduling, while inaccurate automated grading may undermine self-monitoring by providing misleading performance feedback.

However, SDL theory's application to professional education contexts requires careful consideration. SDL emerged from adult education scholarship emphasising voluntary learning driven by intrinsic interest (Knowles, 1975). Professional education differs substantially, in that participation is often motivated partially by credentialing needs, learning outcomes are externally defined by professional bodies, and assessment schedules are fixed rather than flexible. These contextual differences suggest SDL

may manifest differently in professional education than in adult education settings where the theory originated. This study examines whether SDL theory's predictions hold in professional education contexts or whether adaptations are necessary.

2.2.2 Technology Acceptance Model (TAM)

The Technology Acceptance Model, conceptualised by Davis (1989), explains and predicts technology adoption through two primary constructs, Perceived Usefulness (PU), the degree to which a person believes using technology enhances performance on valued tasks, and Perceived Ease of Use (PEOU), the degree to which a person believes using technology will be free of effort. TAM proposes that PEOU influences PU (easier technologies are perceived as more useful), and both constructs influence attitudes toward technology, which in turn shape behavioural intentions to use the technology.

TAM is valuable for framing students' perceptions of AI-generated resources as beneficial or challenging in supporting ACC1A module learning. The model predicts that students will perceive AI as useful if they believe it helps achieve valued learning goals (exam success, conceptual understanding, skill development), and will actually use AI if they perceive it as both useful and easy to use. Conversely, even pedagogically valuable AI will be abandoned if usability barriers create excessive cognitive load or frustration.

Through the TAM lens, data is interpreted to establish whether students' perceptions indicate excessive effort (low PEOU) or minimal barriers to adoption (high PEOU). Bandura's (1997) self-efficacy theory provides a complementary lens to evaluate whether correlation exists between ease of use and students' confidence to leverage AI capabilities. This correlation matters because pedagogically sound Generative AI tools remain underutilised if students lack confidence to engage with them effectively. Conversely, students who believe they can succeed with AI are more likely to persist through initial learning curves and ultimately derive benefits.

Task-technology fit represents another critical TAM-related criterion (Goodhue & Thompson, 1995). This construct examines whether AI tool capabilities align with students' learning task requirements. Even easy-to-use AI will be perceived as not useful if its functionality doesn't match what students need to accomplish. For example, AI providing excellent conceptual explanations will have low perceived

usefulness if students primarily need procedural practice for assessments. Task-technology fit thus mediates the ease of use-usefulness-adoption relationship.

While TAM provides valuable explanatory power for technology adoption, educational applications may require extensions for Accounting based on complexities not present in workplace contexts where TAM originated. Education involves multiple knowledge types (declarative, procedural, conditional), temporal dynamics as learners progress from novice to advanced, and varying task types (concept learning versus skill development versus assessment preparation). This study examines whether TAM's predictions hold uniformly across these dimensions or whether educational contexts require theoretical refinements specifying when and why TAM relationships strengthen or weaken.

2.2.3 Constructivism

Constructivism emphasises active knowledge construction through learner-directed exploration, social interaction, and authentic problem-solving (Bransford et al., 2000; Vygotsky, 1978). Rather than viewing learning as information transmission from expert to novice, constructivism positions learners as active meaning-makers who build understanding by connecting new information to existing knowledge structures, testing hypotheses through authentic activities, and negotiating understanding through social dialogue. Constructivist learning encourages participation, reflection, and self-discovery (Budd, 2005), advocating for immersive and interactive learning environments.

In AI-enhanced education contexts, Puthiyedath (2023) proposes a framework for AI co-creation in pedagogy, where educators combine their understanding of AI capabilities with pedagogical strategies to create authentic learning experiences. For first-year students, especially those from diverse linguistic and academic backgrounds, such a framework provides ways to scaffold understanding of difficult Accounting concepts, using prior knowledge and real-world experiences to build new understanding (Do et al., 2023).

Within Accounting education specifically, AI design principles aligned with constructivism would enable integration of theory with sustained procedural practice and feedback to develop competence. Constructivist AI would not merely deliver information but would engage students in problem-solving activities, provide

scaffolding that gradually withdraws as competence develops, offer authentic contexts connecting concepts to professional practice, and facilitate reflection on learning processes. This represents substantial departure from AI functioning primarily as content delivery mechanism.

Constructivist principles suggest that effective AI implementation should support active knowledge construction through repeated, varied practice with progressively challenging authentic problems. Students would engage not merely in information consumption but in problem-solving production, with AI providing adaptive scaffolding adjusting to individual development, immediate feedback enabling learning from errors, and authentic problems connecting learning to professional Accounting contexts. Assessment alignment would ensure students perceive value in AI-supported activities, while usability standards would enable sustained, focused engagement without technological friction.

However, tensions may emerge between constructivist ideals and practical implementation realities pertaining to the pedagogical architecture of most current Generative AI tools, including the customised tool examined in this study. According to Constructivism, the learner engages actively in inquiry, dialogue, and authentic problem-solving (Vygotsky, 1978; Bransford et al., 2000). Yet the design of Generative AI tools results in students consuming summarised, generated explanations and predetermined questions, instead of constructing knowledge. The Zone of Proximal Development requires that scaffolding be responsive to the learner's evolving understanding (Vygotsky, 1978). Static AI-generated content that lacks adaptability to demonstrated competence does fulfil this requirement. This study examines whether the customised AI tool's design enables or constrains constructivist learning, and what these reveal about the conditions under which AI can be genuinely pedagogically aligned rather than merely pedagogically convenient.

These considerations suggest that constructivism remains valuable but a potentially insufficient framework unless operationalised through intentional, context-sensitive design addressing: (1) extensive procedural practice opportunities with varied, progressively challenging problems; (2) explicit alignment between AI activities and assessment demands ensuring students perceive learning value; (3) usability standards enabling sustained, focused engagement without technological friction; (4)

scaffolding that adjusts to individual learner development rather than remaining static; and (5) authentic problems connecting learning to professional Accounting contexts. This study examines whether these conditions characterise the AI implementation investigated and how their presence or absence shapes learning experiences.

Together, SDL, TAM, and constructivism provide a complementary analytical lens for interpreting the study's findings. SDL foregrounds learner agency and autonomy, while TAM accounts for the influence of system usability and perceived value on students' engagement with AI tools. Constructivism, in turn, situates these interactions within a broader pedagogical context, enabling evaluation of how effectively AI-mediated learning supports meaningful knowledge construction. Considered in relation to one another, these frameworks allow for analysis of both the conditions that enable or hinder self-directed learning in Accounting education.

2.3 The Industrial Revolution and the Rise of AI

2.3.1 Overview

The Fourth Industrial Revolution (4IR) is characterised by rapid advancements in digital technologies such as Artificial Intelligence (AI), machine learning, cloud computing, and robotic automation, fundamentally reshaping how people live, learn, and work (Aboderin & Havenga, 2024). As higher education institutions (HEIs) prepare students for this evolving landscape, there is growing recognition that traditional pedagogical approaches may require adaptation or augmentation. Innovative teaching and learning strategies are being explored to equip students with cognitive, technical, and critical thinking skills necessary for success in an AI-integrated world.

Aboderin and Havenga (2024) propose a framework outlining essential competencies required for 4IR and identifying pedagogical strategies to enhance student preparedness. These include AI literacy, critical thinking, problem-solving, and adaptability, posited as crucial for students navigating a technologically driven economy (Aboderin & Havenga, 2024). They highlight evidence-based teaching, AI-enhanced learning environments, and cooperative learning as approaches potentially promoting meaningful engagement and skill mastery. Within our local context, Muzuva (2024) argues that for South African Higher Education Institutions (SAHEIs) to effectively integrate 4IR principles, technology-enhanced learning methods, particularly AI-driven innovations, may be essential in addressing educational gaps

and personalising student learning experiences. This aligns with evidence-based teaching approaches focusing on active, student-centered learning, data-driven feedback, and development of higher-order cognitive skills (Malott et al., 2014).

Zhou and Schofield (2024) contend that when integrated with innovative pedagogy such as cooperative learning and adaptive feedback mechanisms, Generative AI has potential to enhance student learning and skill acquisition. Similarly, Hazari (2024) asserts that AI literacy is not only essential for navigating 4IR but also fosters critical thinking and innovation among students, preparing them for dynamic and evolving professional landscapes.

Emerging literature suggests Generative AI may offer transformative potential in higher education, though evidence regarding effectiveness and appropriate integration remains contested (Selwyn, 2019; Watanabe, 2024). As a result, policy frameworks are being formulated based on research, such as South Africa's National AI Policy Framework, which advocates for AI integration into curriculum and for academia-industry collaboration to understand AI's application in professional contexts (Department of Communication & Digital Technologies, 2024). However, implementation challenges, equity concerns, and questions about actual versus perceived learning gains warrant cautious, evidence-based adoption rather than uncritical enthusiasm (Selwyn, 2019).

Student learning is influenced by complex interplay between perceptions of the learning environment, abilities, and pedagogical strategies employed by educators (Biggs, 1999, cited in Chan & Hu, 2023). This highlights the importance of student-centered AI applications, which adapt to individual learning needs and foster engagement, mastery, and critical thinking. By exploring first-year Accounting students' experiences with AI-generated lecture summaries and question pathways, this study contributes to growing discourse on AI's pedagogical value. The study provides empirical insights into how AI-supported learning environments may enhance engagement, improve learning outcomes, and develop essential skills, while also examining challenges and limitations constraining effectiveness.

Furthermore, the outcomes offer guidance to policymakers, institutional leaders, and academics on practical adoption of AI-driven strategies, ensuring responsible and effective integration of 4IR technologies within South African higher education

(Muzuva, 2024). These insights are critical for strategic curriculum design, reinforcing the study's significance in the evolving educational landscape (Bobula, 2024).

2.3.2 AI and Its Role in the Fourth and Fifth Industrial Revolutions (4IR and 5IR)
 Revolutions in industry have been occurring since 1784 (Chen et al., 2023). Figure 1 provides an overview of these revolutions through time and the defining characteristics of each.

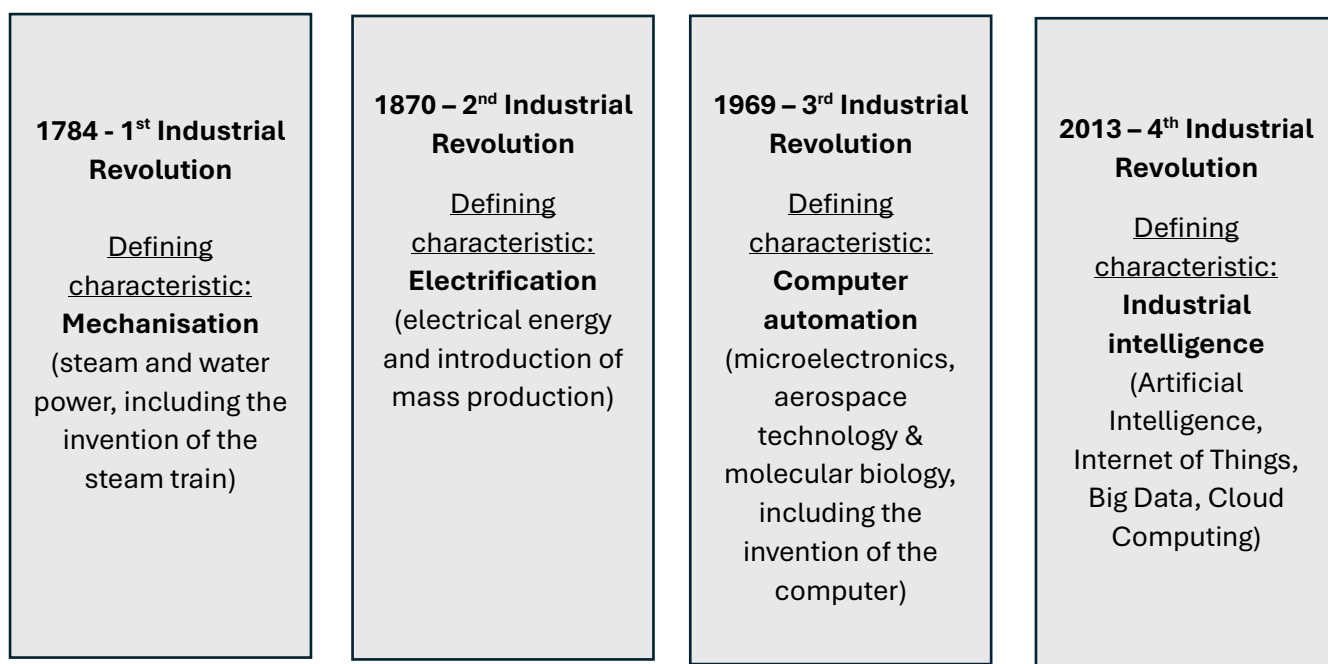


Figure 1: The Revolution of Industry, adapted from Chen et al (2023)

Smart technology, Artificial Intelligence, Robotics and Algorithms (STARA) are defining features of the 4IR (Oosthuizen, 2022). Advancements include automation, Artificial Intelligence, biotechnology, robotics, cybersecurity, Internet of Things, driverless vehicles, quantum computing, blockchain, and 3D printing (Simmons & McLean, 2020). Due to rapid technological advancements and their potential to be more efficient than manual labour, warnings from figures like Bill Gates and Stephen Hawking, along with predictions from researchers, suggested that a third of jobs that existed more than 10 years ago would be replaced by STARA by 2025 (Brougham & Haar, 2018).

Fast-forward to 2025, the rise of STARA has instead augmented and enhanced many aspects of work and life. Increasingly, the 4IR is perpetuating the creation of jobs that did not exist before. The introduction of automated ships is one such example, requiring specialized skills in the form of an Industry 4.0 seafarer to operate

sophisticated technology (Simmons & McLean, 2020). Whilst AI will displace certain roles, it is estimated that this will impact 92 million jobs, but 170 million new roles will be created (World Economic Forum, 2025). It is at this juncture that the positioning of AI as the main driver of the 4IR is understood, and its transformational impact on industry. AI's influence is felt both at an individual level and across all industries, from manufacturing to service, retail, and education. Utilising deep learning, sophisticated AI tools are trained to enable intelligent or smart industries and societies through data mining, integration, and automation (Chen et al., 2023).

Whilst AI is revolutionising industry, the statistics provided by the World Economic Forum regarding job creation highlight that there remains a place for human capacity and skill to work alongside AI, which is where the Fifth Industrial Revolution comes in.

Research regarding when the Fifth Industrial Revolution began is unclear. Authors such as Lachvajderova and Kadarova (2022) and Plesa et al. (2024) indicate that we are moving towards the Fifth Industrial Revolution (5IR), whilst others like Golic (2019) and Noble et al. (2022) indicate that we are already in the 5IR. Whether this evolution is still in progress or represents the current state, what remains evident is that technology, specifically AI, is advancing at a rapid pace and continues to disrupt industry and daily life.

Figure 2 below depicts AI's influence on major industries, along with examples.

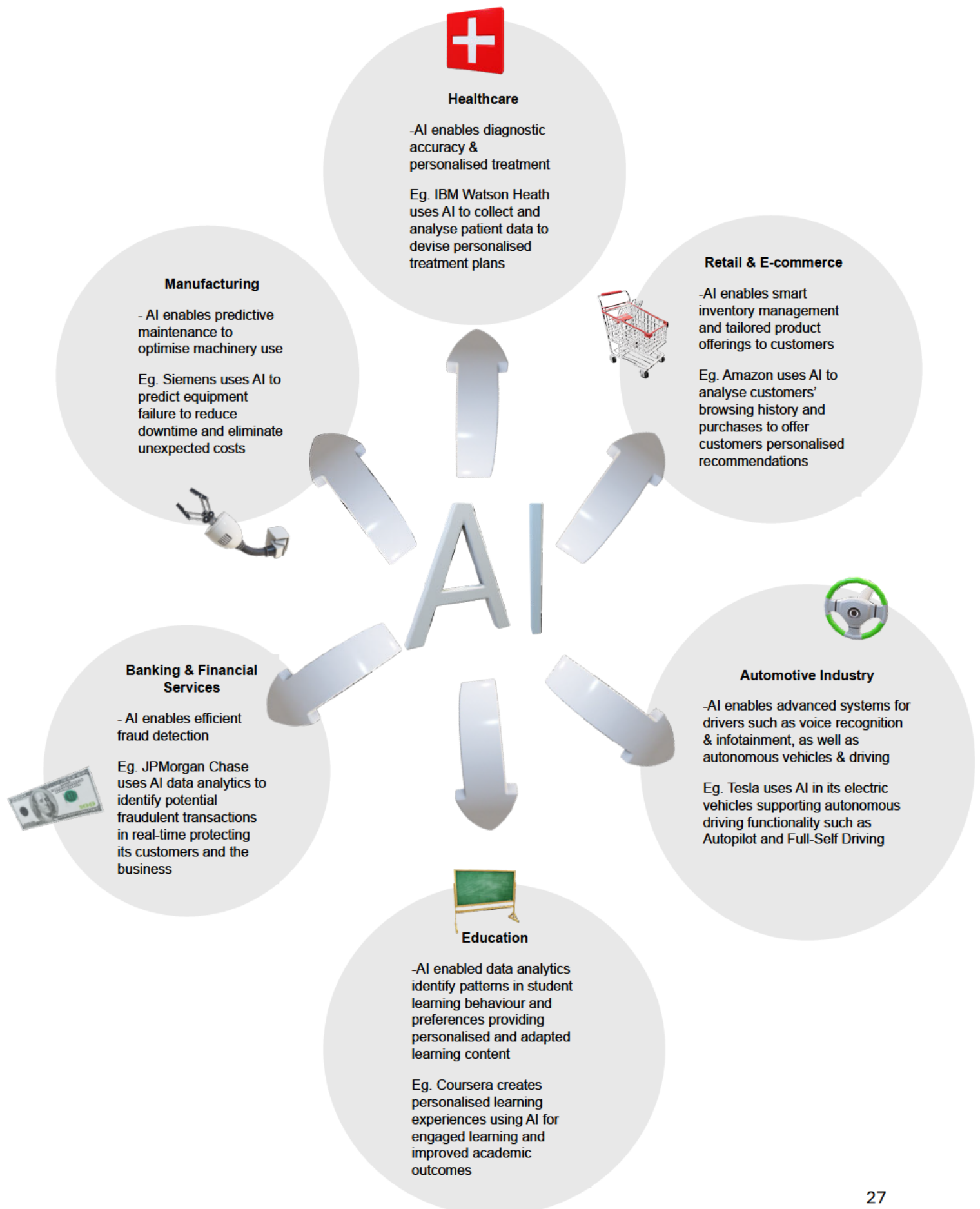


Figure 2: AI's influence on industry (adapted from Shuliak, 2025)

With the need for greater personalisation and efficiency, the ways in which humans and machines interact are constantly changing and being redefined. There is now greater emphasis on collaboration. Individuals are more comfortable expressing their individuality, demanding products and services that are personalised to reflect their unique identities. 5IR is therefore characterised as having collaborative engagement between AI and humans resulting in personalisation that possesses the human touch to deliver on this individuality (Golic, 2019). Another key focus of the 5IR is increased societal wellbeing and environmental sustainability (Noble et al., 2022).

Based on AI's impact on virtually every industry within the 4IR and into the 5IR, it is apparent that there is demand for the acquisition of new skill sets for human capital to adapt to changes within industry. This necessitates a level of agility from the workforce like never before. Moreover, the concept of lifelong learning and its integration in the workplace has become essential. This is echoed in the Future of Jobs report by the World Economic Forum (2020). The report indicates that 40% of the workforce will require reskilling six months into employment, with on-the-job skill acquisition playing a vital role (World Economic Forum, 2020).

Beyond skills such as AI literacy, critical thinking, and problem-solving which are advocated for in the 4IR, skills such as creativity, empathy, citizen engagement skills, and ethical decision-making are regarded as equally important for the 5IR (Lachvajderova & Kadarova, 2022; Plesa et al., 2024). The World Economic Forum summarises the core skills that are required in industry within the present day, alongside skills that will be of increasing use by 2030 in South Africa (World Economic Forum, 2025):

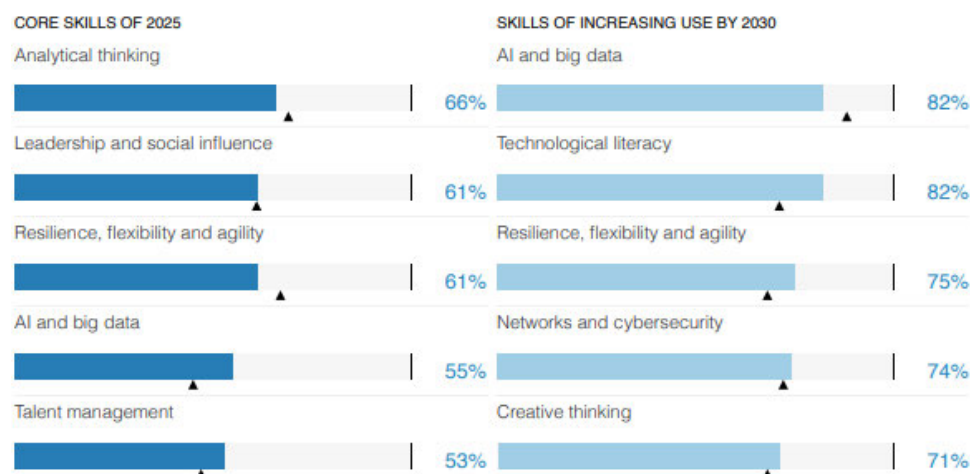


Figure 3: Skills of increasing use in South Africa (World Economic Forum, 2025, p.196)

These statistics and the constant change in expectations regarding skills required by the workforce exhibit the need for higher education institutions to stay abreast of current and future trends in skill demand, to adequately prepare students for the world of work. The South African National AI Policy Framework advocates for the incorporation of AI into curricula to aid in capacity and skills development of students (Department of Communications & Digital Technologies, 2024). This translates into the need for active teaching and learning strategies, along with the adoption of AI technology to achieve this end (Aboderin & Havenga, 2024). This innovation in pedagogy, which is called for within higher education, illustrates the demands that the evolution of the 4IR is placing on higher education, which is discussed in more detail in the next section.

2.3.3 The Influence of the Fourth Industrial Revolution on Higher Education

In this section, literature is presented illustrating how higher education is responding to the opportunities and demands presented by 4IR. The main driver of influence and innovation in pedagogy in higher education is the incorporation of 4IR technology into practice. Opportunities available through 4IR technologies include transformation of assessment practices, innovative learning technologies, and lecturer development (Singaram et al., 2023). Its implementation, particularly through the use of AI and data analytics, may improve teaching and learning, as well as administrative functions (Samuels & Singh, 2025).

Examples of such technology include customised AI learning systems which enable personalised support for students by analysing students' performance, blockchain technology which enhances the integrity and quality of student academic data, and the Internet of Things (IoT) which enables integrated resources and infrastructure (Samuels & Singh, 2025). Intelligent Tutoring Systems and AI Chatbots are further examples of technology tools that provide students with interactive resources and learning support (Lubinga et al., 2023). These innovative technology tools have potential to enhance students' learning experiences, improve academic performance, and address skills gaps (Shenkoya & Kim, 2023).

Embedding problem-based learning within curricula and teaching and learning are key for the 4IR. Research indicates that the use of AI to support problem-based learning may improve students' overall performance. In a study by Habibah et al. (2025),

empirical evidence is presented of how an AI tool enhances problem-based learning by supporting students' learning through scaffolding, improving critical thinking, and supporting self-directed learning.

4IR calls for reimagining curricula. University of Cape Town, Stellenbosch University, and the University of Pretoria have included electives and core modules into some of their qualifications that equip students with requisite skills for 4IR such as analytical skills and design thinking (Lubinga et al., 2023). Design thinking teaches students how to address complex, dynamic real-world problems (Gleason, 2018). Case studies of ShanghaiTech in China and Yale-NUS College in Singapore illustrate how global institutions of higher learning are overhauling their curriculum to ensure relevance and adequate student preparation.

ShanghaiTech's Design Thinking module incorporates a "Desert Island" challenge which requires students to employ critical thinking to evaluate initial assumptions, review how these assumptions frame the problem, reframe their assumptions, and evaluate how this may impact individuals in the given scenario (Gleason, 2018). This process establishes students' connection between critical thinking and human-centeredness. At Yale-NUS College in Singapore, students enrolled in the Mathematics and Computational Science module design robots and create software start-ups, allowing the institution to act as an entrepreneurial incubator for its students (Gleason, 2018). Curriculum transformation is necessary to empower students with the required competencies to engage with rapidly evolving 4IR technologies, and these case studies exemplify how this may be achieved in higher education.

Another area of opportunity presented by 4IR technology is research, enabling a more dynamic and multidisciplinary approach (Vurayai, 2025). The capitalisation of the opportunity to digitise various elements of university operations leads to innovative business models that allow greater competitive advantage and therefore universities' sustainability within the higher education landscape (Shenkoya & Kim, 2023).

The demands of 4IR on higher education require student knowledge of and preparedness for the use of AI and IoT, and institutional preparedness (curriculum, learning environment, technological infrastructure, and training) for successful implementation and adoption of 4IR technologies at universities (Al-Maskari et al., 2022). The absence of the aforementioned aspects creates barriers for 4IR technology

adoption and can exacerbate the digital divide, particularly in a country like South Africa (Samuels & Singh, 2025). Partnerships across universities, and with industry, are recommended to inform curriculum designers on how to embed AI, IoT, data science, cloud computing, and machine learning into modules, whilst also enabling interdisciplinary connections between modules (Al-Maskari et al., 2022).

In conclusion, 4IR, which continues to evolve, has far-reaching effects on higher education, requiring transformation at multiple levels, with adoption depending on development of new skills (Lubinga et al., 2023). This places faculty or lecturer training and development as a top priority such that lecturers are able to strike the balance between knowledge dissemination and the development of students' skills for the 4IR and beyond (Samuels & Singh, 2025). This study is therefore timely and appropriate in uncovering empirical evidence of how that balance may be obtained through a case study that explores students' experiences of a customised Generative AI tool integrated into pedagogy.

2.3.4 The Influence of the Fourth Industrial Revolution on Accounting Education

Accounting functions are becoming automated for greater efficiency through the technological advancements brought about by the 4IR (Mthimkhulu et al., 2024). Roles are being redefined in the profession where the focus of the job shifts away from manual tasks to one of analysis and interpretation of data (Brands et al., 2024). This level of automation requires university students to be equipped with technical and interpersonal ethical skills to scrutinise and act as gatekeepers for data from automated systems, business skills such as strategic thinking, soft skills such as critical thinking and problem-solving, and digital and data skills such as accounting digitisation and data analytics (Tsiligiris & Bowyer, 2021).

Karsten et al. (2020) therefore advocate for holistic development of Accounting students through deep learning that develops their cognitive, interpersonal, and intrapersonal skill sets. A study by Landsberg and van den Berg (2023) revealed that gaps in Accounting curricula amongst the top 5 universities in South Africa related to digital and relational acumen. In this regard, it is especially encouraged for universities to build 4IR digital skills into curricula such as big data, data analytics, AI, blockchain, cloud computing, basic coding, and cybersecurity.

In conclusion, for Accounting curricula to meet the demands of 4IR and ensure that students are adequately prepared for the changes in industry, digital skills along with key soft skills need to be embedded into pedagogy. This provides direct justification for this study which examines how a customised Generative AI tool shapes first-year Accounting students' understanding of learning outcomes and skill development in the ACC1A module.

2.3.5 The Connection Between the Fourth Industrial Revolution and the Study's Objectives

The discussion presented in this section highlights the profound impact that 4IR has had across industries, with the rise of AI being the main driver. The demands of 4IR on higher education require student knowledge of and preparedness for the use of AI and IoT, and institutional preparedness (curriculum, learning environment, technological infrastructure, and training) for successful implementation and adoption of 4IR technologies at universities (Al-Maskari et al., 2022). This strikes at the heart of this study as the objectives align with the demands that 4IR places on universities.

The empirical evidence uncovered presents a case study of how universities may respond to demands placed by 4IR, exploring potential for leveraging 4IR technology by embedding AI into teaching and learning. Through the exploration of students' experiences of engaging with AI-generated lecture summaries and pathway questions, thereby establishing benefits and challenges experienced, this objective of the study aligns with assessment of 4IR demands related to student preparedness for the use of AI in higher education.

Research suggests that when 4IR technologies, such as AI, are embedded in curricula, they may enhance students' learning experiences, improve academic performance, and address skills gaps, preparing students for the continued evolution of the 4IR (Shenkoya & Kim, 2023). This aligns with the objective of the case study which examines and provides evidence of how a customised Generative AI tool shapes students' understanding of learning outcomes and skill development in the ACC1A module.

The integration of AI technology in higher education offers opportunities to reimagine pedagogy through personalisation, adaptive feedback, and evidence-based instructional strategies (Aboderin & Havenga, 2024; Zhou & Schofield, 2024). An

evaluation of a customised generative AI tool used in an Accounting module in this case study is therefore timely in providing empirical evidence of how Accounting education can be reimagined through the use of AI, supporting first-year students with the building blocks for a profession that is being revolutionised through 4IR.

In summary, the connection between 4IR and the objectives of the study resides in the alignment of study findings that may reinforce research positioning AI as potential catalyst for curriculum reform in higher education, and potentially central to the development of students' skills for an automated, digitised, and personalised world. By evaluating benefits and challenges of integrating AI-generated resources into teaching and learning in a first-year Accounting module within the South African higher education context, the outcomes of the study may inform strategic curriculum design, thereby responding to demands of 4IR and the need for innovative teaching and learning practice to build essential skill sets.

2.4 AI, Large Language Models and ChatBots

2.4.1 Overview

The Fourth Industrial Revolution (4IR) has significantly influenced higher education, accelerating the adoption of Artificial Intelligence (AI) in teaching and learning. AI-driven technologies, particularly Large Language Models (LLMs) such as ChatGPT, have transformed pedagogical methodologies by enhancing student engagement and reshaping the design of learning materials (Nguyen et al., 2024). The COVID-19 pandemic further catalysed this integration by necessitating innovative approaches to online teaching and learning (Funda & Piderit, 2024).

AI, broadly defined as machines exhibiting intelligent, human-like behaviour, has evolved to include sophisticated systems such as LLMs, a category of Generative AI that employs predictive modelling to analyse and generate human-like content (De Villiers-Botha, 2024; Carrol & Borycz, 2024). ChatGPT, introduced in 2022, has experienced rapid global adoption, leading to the integration of AI-powered tools into mainstream applications such as Microsoft Copilot (Moore & Lookadoo, 2024; Singh, 2023).

Chatbots such as ChatGPT simulate human conversation using large datasets derived from books, webpages, and articles (Stohr et al., 2024). Their interactive and conversational nature supports student engagement and motivation when

incorporated into teaching and learning practices (Labadze et al., 2023). Additionally, universities globally are embedding chatbots into pedagogy to support student learning through concept clarification, administrative support, and skills development (El Mourabit et al., 2025).

From an educational perspective, AI demonstrates potential to improve teaching quality and student learning efficiency (Funda & Piderit, 2024). However, its integration remains an area of ongoing inquiry, particularly regarding educators' preparedness and the conditions under which AI meaningfully enhances learning (Celik, 2023, cited in Bobula, 2024).

2.4.2 Classification of the Customised Generative AI Tool Under Study

AI applications in higher education are broadly categorised into: (i) education management and delivery, (ii) learning and assessment, (iii) empowering teachers, and (iv) lifelong learning (Miao et al., 2021, cited in De Villiers-Botha, 2024). This study focuses on learning and assessment, and teacher empowerment.

The customised Generative AI tool examined in this study extends beyond conventional LLMs by incorporating subject-matter expertise to produce contextually relevant outputs (Memarian & Doleck, 2024). These outputs include lecture summaries and AI-generated pathway questions derived from recorded lectures, which guide students through branching scenarios aligned with learning outcomes (Vasquez-Parra et al., 2024; D2L, 2024).

Across the literature, a core pedagogical contribution of AI lies in its ability to support personalised, adaptive, and timely feedback mechanisms that facilitate self-regulated learning and deeper engagement with content. This study examines how such capabilities manifest within a customised AI system and influence student learning experiences.

Given the limited empirical evidence on customised, lecturer-integrated AI tools, this study contributes to understanding how such systems support teaching and learning and inform curriculum design (De Villiers-Botha, 2024). The findings of the study address this gap by presenting evidence of how AI can support teaching and learning, informing strategic curriculum design.

2.5 Student Engagement with AI and Benefits for Incorporating AI into Learning

Studies demonstrate that AI use in higher education spans multiple purposes, with conceptual clarification, assignment support, and exam preparation emerging as primary uses across diverse contexts. The geographic distribution of research summarised in Table 1, spanning Vietnam, Poland, Denmark, South Africa, and multiple other contexts, suggests AI adoption is a global phenomenon not limited to technologically advanced nations. However, most studies document usage patterns and perceived benefits through self-report measures; fewer examine actual learning outcomes through objective assessment instruments, representing a significant gap in current literature.

AI Tool	Usage	Benefits	Authors
ChatGPT	74.5% used ChatGPT; 82.2% for learning, 75.3% for info searches, 43.8% for problem-solving, 35.6% text editing, 32.9% content creation, 20.8% entertainment, 9.6% other	Supports learning, information retrieval, problem-solving, content generation, and editing	Nguyen et al. (2024)
Generative AI	63% used AI to find solutions; 45% to understand difficult concepts	Improves conceptual understanding and supports independent problem-solving	Walczak & Cellary (2023)
Gemini, Elicit, Heuristica	Gemini: idea formulation; Elicit: summaries/lit reviews; Heuristica: mind maps	Enhances creativity, supports academic research, visualises complex ideas	Seedan (2025)
Grammarly	Academic writing aid	Instant feedback on grammar, clarity, engagement, and delivery	Abu Qub'a et al. (2024)
Adobe Firefly	Multimedia content generation using prompts	Provides instant creation of images, videos, and text for learning and presentation	Kumar & Sekhar (2025)
Various AI tools incl. ChatGPT	Clarify academic concepts, formulate ideas, essay structuring, writing support, time saving, paraphrasing, summarising, referencing, study aid	Enhances understanding, academic writing, efficiency, and academic integrity	Bosch et al. (2023)

Generative AI	Expand content understanding, summarising, idea generation	Supports comprehension, research, and knowledge building	Razmerita (2024)
AI tools for various disciplines	Brainstorming, summarising, writing, coding, admin, math problem-solving	Multidisciplinary support: enhances creativity, programming, technical understanding, language learning, and admin tasks	Schei et al. (2024)
ChatGPT	Querying, getting answers, engaging with definitions, lesson prep, basic level verification	Promotes engagement, preparation, and confidence; allows teachers to focus on higher-order teaching	Korkmaz Guler et al. (2024)
AE BOT (AI-powered assistant)	Personalised Accounting support via curriculum-aligned, theory-based prompts	Context-specific guidance, personalised learning, improved student engagement in discipline-specific content	Coetzee (2024)

Table 1: Tabulated uses of AI in higher education and the associated benefits (Author collation)

Additionally, existing research predominantly focuses on what students do with AI tools and what they perceive as beneficial, with limited investigation of why certain uses prove effective or ineffective, what mechanisms mediate effectiveness, or under what conditions benefits materialise. The literature reveals high adoption rates and positive perceptions but provides insufficient evidence for claims about actual learning improvement, skill development, or knowledge transfer. This gap justifies mixed-methods investigations examining not only adoption patterns but also the pedagogical mechanisms through which AI supports or constrains learning.

The literature presented in this section reveals potential benefits of AI in education but, more importantly, emphasises that students use AI tools for diverse purposes beyond merely finding answers for assessments, they engage with learning outcomes and support higher-order learning skills aligned with Bloom's taxonomy (Razmerita, 2024). Owing to AI's widespread adoption, universities now face a strategic choice to support students in utilising AI effectively through evidence-based policies and pedagogical integration, or risk disadvantaging students who will encounter AI-integrated workplaces regardless of academic preparation.

Those who choose to support effective AI integration should leverage AI's capabilities for immediate feedback and self-assessment functionality to develop students' self-regulated learning skills through curricula encouraging critical thinking and exploration via adaptive teaching and learning strategies (Xia et al., 2024). This notion supports the co-creation framework of Puthiyedath (2023), expounded in the theoretical framework section of this dissertation, which advocates for a relational approach to teaching that is open, collaborative, democratic, embraces deep discussion and learning, and is responsive to student needs (Bovill, 2020). Such frameworks are critical for effective AI integration in higher education, though implementation challenges documented in Section 2.6 suggest integration requires careful planning rather than simple technology deployment.

There is substantial need for qualitative research pertaining to AI tools' impact on students' learning strategies, development of critical thinking, problem-solving, and creativity, in addition to development of theoretical models to better understand their use and integration for effective and responsible use within educational frameworks (Schei et al., 2024). The authors also highlight literature gaps across continents, including Africa. This provides justification for a study of this nature, which contributes directly to this body of knowledge and addresses literature gaps identified through exploration of students' learning experiences supported by a customised Generative AI tool. The empirical evidence informs understanding of AI tools' pedagogical impact on tertiary students' learning, student engagement, mastery of learning outcomes, and skill development, from students' perspectives within our local context.

2.6 Challenges and Barriers to the Effective Adoption of AI in Higher Education

Within the South African Context

2.6.1 Diversity Versus Equity of Delivery

South Africa's higher education landscape includes a variety of institutions, such as public universities, Technical and Vocational Education and Training (TVET) colleges, and private higher education providers, all tasked with delivering quality education while addressing the socio-economic disparities that exist in the country (Patel & Ragolane, 2024). Research positions AI as a tool that may support higher educational institutions in South Africa to achieve this end. Patel and Ragolane (2024) advocate for the integration of AI in South African higher education, emphasising potential

benefits such as personalised learning, improved administrative efficiency, and data-driven decision-making as possible solutions to equity issues in South African higher education.

This particular study is located within a private higher education institution, which operates in a competitive educational market and prioritises innovation in teaching and learning. This environment is therefore appropriate for a case study of this nature to assess if the findings of the study align with current literature, as the private institution, whilst less resource-constrained and can more readily deploy a customised Generative AI tool, still has to contend with a student profile characterised by varied socio-economic backgrounds. Therefore, challenges such as diverse student academic preparedness, large class sizes, multilingualism, inadequate curriculum design, and variation in academic ability may still hinder the customised Generative AI tool's effective adoption (Funda & Piderit, 2024).

Disparities in AI awareness represent another factor. Interestingly, this challenge is not limited to South Africa but is also present in the United States, where teenagers from wealthier households are significantly more aware of AI tools compared to those from lower-income households. These disparities highlight the importance of considering prior exposure to AI tools, and ensuring that students are afforded requisite training and support. Training has to meet the needs of those entering tertiary education who are already conversant and will expect AI to continue to play a role in their academic journeys, as well as those who lack exposure altogether (Moore & Lookadoo, 2024). It is based on this burden, amongst other factors, that the continent has a low success rate with technology adoption, as it perpetuates concerns that the inability to strike such a balance could exacerbate existing social inequalities (Funda & Piderit, 2024). The authors therefore advocate for a curriculum overhaul to achieve equity in delivery (Funda & Piderit, 2024).

These factors underscore the necessity of this study, which explores students' experiences with structured learning support and interactive questioning through a customised Generative AI tool, and illuminates how it may address disparities in AI exposure. It also sheds light on the local nuances of Generative AI adoption and use, thereby informing future AI implementations in higher education.

To alleviate some of these challenges within our local context, the country is encouraged to adopt best practices from nations like Uganda and Ethiopia, where AI adoption has shown success within the African context (Funda & Piderit, 2024). Singh (2023) encourages a responsible approach to AI adoption in education, emphasising its potential when used appropriately. De Villiers-Botha (2024) suggests strategies to minimise discrimination and exclusion in AI tool application, which could mitigate the challenges of AI integration within South African higher education (see Figure 4 below).

Challenge	Mitigation Strategy
Lack of hardware, internet connectivity, and data	Identify and assist students without access to adequate resources
Disabilities or special needs students	Make provisions for students with disabilities or special needs to ensure equitable access to AI tools
Bias and discrimination	Validate AI tools to eliminate bias, ensuring the data is representative of diverse social and cultural backgrounds
Language of instruction	Train AI tools in multiple languages to support multilingual usage and reduce dominant cultural bias

**Figure 4: Strategies to minimise discrimination in AI tools' application in SAHE
adapted from De Villiers-Botha (2024)**

In summary, diversity in the profile of students enrolled in terms of socio-economic backgrounds, AI awareness, and preparedness are all important factors for South African higher education institutions to be cognisant of when incorporating AI into teaching and learning. A strategic approach to AI implementation is needed. This is where the importance of robust policy frameworks comes in to ensure that these factors do not become barriers that hinder AI's effective implementation and adoption at institutions of higher learning. Careful mitigation strategies, guided by policies, along with curriculum that embeds AI use, will ensure barriers are overcome. This research is therefore timely in presenting a case study of the use of a Generative AI tool in higher education, presenting evidence of how universities may strike the balance between managing diversity to ensure equitable delivery of teaching and learning by leveraging the use of AI.

2.6.2 Policy Frameworks

Challenges, such as inadequate training for lecturers, the absence of a regulatory framework, and budget constraints, have been identified as obstacles to AI's successful adoption in South Africa (Patel & Ragolane, 2024). Addressing these barriers will require strategic efforts by higher education institutions for effective integration of AI. Effective policies and guidelines for students' use of AI, aligned to faculty goals and learning outcomes, as well as access and privacy protocols to safeguard students' data are key to the policy discussion (Moore & Lookadoo, 2024).

The South African AI Policy Framework is therefore a step in the right direction to guide South African universities on how to address challenges and opportunities in a holistic and sustainable manner (Department of Communications & Digital Technologies, 2024). However, authors such as Dube (2025) criticise the framework for lacking clarity regarding its implementation, recommending a phased approach, ongoing legislative updates, and monitoring initiatives. Naidoo and Pillay (2018), cited by Ajani (2024), advocate for higher education institutions to implement robust governance frameworks and policy guidelines which afford this level of clarity to ensure the ethical application of AI and mitigate against potential risks.

Several other authors, such as Hazari (2024) and De Villiers-Botha (2024), support this viewpoint, also advocating for universities to implement comprehensive privacy policies to protect students and avoid confusion and panic amongst both students and faculty (Moore & Lookadoo, 2024). UNESCO's Recommendation on the Ethics of Artificial Intelligence provides essential principles for the inclusive, transparent, and accountable adoption of AI. According to AllahRakha (2024, p.32), it serves to establish global ethical standards, foster public trust in AI technologies, drive responsible innovation, and catalyse international cooperation in AI governance.

The policy framework which guides the use of Generative AI at Emeritus College is the Teaching and Learning Strategy and the South African AI Policy Framework. This Strategy outlines the values and principles of teaching and learning, quality expectations, graduate attributes the institution wishes to develop in its students, and the quality assurance framework for the institution (The IIE, 2025).

AI policies also have an important role to play in maintaining the academic integrity of universities by eliminating AI abuse and promoting its ethical use. According to

Evangelista (2025), policies should outline how assessments can be restructured to assess critical thinking and problem-solving, presenting innovative strategies to assess students, along with the incorporation of AI detection tools in practice. Such robust policies address the issue of originality in students' work, ensuring that students do not misuse AI and present authentic work. Students who rely too heavily on AI when completing assessments hinder their development of critical thinking and creativity, as they are not engaging with the assessment at hand, but instead focusing more on effective prompts to generate the responses needed (Ivanov, 2023). This also presents students with a false sense of module outcome achievement.

A few examples of universities that have transformed their assessment practice to uphold academic integrity include Stanford University, Duke University, and University of Sydney, whereby assessments take the form of interactive project-based assessments and oral exams to improve authenticity of students' work (Evangelista, 2025). Alternate viewpoints, such as those from Luo (2024), recommend viewing originality through the lens of collaboration, whereby students and AI collaborate to achieve original work measured in varying degrees. Policies that align to this thinking do not view originality from the angle of misconduct alone, but instead clarify what aspects of assessment should be original, allowing flexibility to assess originality based on the discipline and learning outcomes to be achieved (Luo, 2024).

An example of this balanced approach is an assessment which includes original work through application questions and questions that promote students' collaboration with AI, to conduct data analysis or produce a video for a portion of the assessment mark (Ivanov, 2023). This approach ensures that students are still able to develop critical thinking and creativity, whilst also building their digital literacy through the responsible use of AI. Regardless of which school of thought universities decide to align with, the fact remains that policies are critical to frame both students' and faculty's use of AI in higher education.

Formulating and instituting AI policies are, however, not without their own challenges as they have to consider the changing legal and technological criteria balanced against the need to ensure equitable academic delivery for all students (Moore & Lookadoo, 2024). Moreover, for the implementation of AI in higher education to be successful and give rise to effective policies, policymakers also need to accept and support its very

integration. According to Patel and Ragolane (2024), acceptance by policymakers can lead to increased student engagement and support the ethical use of AI.

Javed et al. (2022), cited in Hazari (2024), posit that AI ethics training and education is critical to ensure that student behaviour aligns to higher education institutions' policies on AI use. Moore and Lookadoo (2024) present a framework for the implementation of policy advising that policy should be written for students using plain language, avoiding naming tools, being cognisant of negative connotations in the language used in the policy, and being mindful about the positioning of AI usage. For policies to align to pedagogical goals, Moore and Lookadoo (2024) advise that AI should be explained transparently, to align communication to the faculty's syllabus, to shift the focus from performance to learning, and to be clear in assignment instructions.

With the release of the South African AI Policy Framework, institutions are now better equipped to utilise the framework for effective implementation. By aligning AI implementation strategies to the pillars of the South African AI Policy Framework, higher education institutions can build AI talent pipelines, enhance digital readiness, drive AI research and innovation, ensure ethical and inclusive AI use, promote transparency and trust, and align AI development with societal values (Department of Communications & Digital Technologies, 2024).

In a study of this nature which explores students' learning in terms of their engagement, mastery of learning outcomes, and skills development within the South African context, policy frameworks are relevant in that transparent guidelines reduce confusion, promote equitable access, and shift the focus from performance to meaningful learning (Moore and Lookadoo, 2024). This study explores the learning experiences of students in the ACC1A module, providing empirical evidence related to the benefits and challenges of how Generative AI shapes students' understanding of the module outcomes and the development of skills. Thus, the evidence-based insights gained from the study serve to inform revisions of the current Teaching and Learning Strategy at Emeritus College, specifically related to the use of technology in teaching and learning and promotion of diversity, which are the two constructivist concepts that constitute the foundation of the teaching and learning approach at the institution (The IIE, 2025). The outcomes of the study therefore may advance the

quality and equity in teaching and learning at Emeritus College, and provide a blueprint for AI's adoption more broadly across other institutions of higher learning.

2.6.3 Inertia

Advancements in technology are synonymous with disruption, and thus AI is no different from when calculators, emails, and search engines emerged in academia (Moore & Lookadoo, 2024). It must also be noted that despite the ongoing debate regarding the ethical use of AI, many students and organisations are already utilizing AI and will continue to do so. However, whilst this is so, some organisations have also banned the use of AI, such as ChatGPT (Moore & Lookadoo, 2024). Thus, the debate regarding the pros and cons of AI use persists, even beyond academia and into the workplace. The very nature of change brought about by AI's disruption and the associated debates results in inertia.

Lack of teaching experience, institutional support, and socio-cultural context are all contributing factors that lead to disinterest and hinder the adoption of AI integration into pedagogical practices (Funda & Piderit, 2024). Negative aspects of AI use including limited interaction, misleading and outdated responses, insufficient personalised feedback, and difficulty in adapting to technology are further contributing factors (Gokceaslan et al., 2024). For lecturers, apathy to adopt AI into pedagogical practice includes increased student plagiarism, under-preparedness of students to use AI, and the complex nature of incorporating AI into effective teaching and learning (Gokceaslan et al., 2024).

Holmes et al. (2021), cited in Patel and Ragolane (2024), highlight that lecturers' and students' perceptions are essential for the adoption of AI tools. Such barriers, that represent negative aspects of AI integration in higher education, when given priority in decision-making, will hamper any efforts to integrate AI into practice. What must be realised by higher education institutions is that opportunistic behaviour by staff and students existed and continues to do so, long before and outside of AI use. Negative aspects related to student cheating and strict enrolment criteria are but two examples. These are not exacerbated by AI, but what separates the two is the medium through which it may occur. The common denominator is, however, human behaviour. This is what needs to be controlled and managed.

The negative aspects of AI integration therefore need to be contrasted against the negative aspects of university contexts excluding AI (Ivanov, 2023). Which is worse? It can be argued that the latter presents greater disadvantage. It is therefore advocated that by addressing these concerns through policies, user-friendly designs, and pedagogical alignment, institutions can enhance the willingness of both students and lecturers to engage with AI tools ethically for improved teaching and learning.

2.6.4 Data Privacy and Security

One of the key challenges of AI integration in higher education relates to the ethical use of AI, including data privacy and security (Xia et al., 2024). Whilst the SA AI Policy Framework advocates for existing data protection regulations to be strengthened, privacy remains a sensitive topic within the discourse of AI use in HEIs. Universities hold a substantial amount of data related to students, staff, and faculty. The risk of data leakage, data misuse, algorithmic bias, and invasive methods, such as proctoring, heightens concerns of AI's implementation in higher education (Xue et al., 2025).

It is therefore imperative that universities adopt rigorous data governance frameworks and remain transparent regarding what data is being collected, how it is to be used, and how it will be shared (Yang & Beil, 2024). In addition, regular policy reviews and updates, as well as ongoing training, are key to ensuring that data remains secure (Yang & Beil, 2024).

2.6.5 Hallucinations and Bias

In addition to these challenges, inconsistencies, hallucinations, and biases are further limitations identified, requiring students to be critical and cautious about the information generated by AI (Swindell et al., 2024). According to Bubeck et al. (2023), hallucinations can be closed-domain or open-domain hallucinations (Walczak & Cellary, 2023). Closed-domain hallucinations are infrequent and occur within a specific context, making the inaccuracy easily identifiable; however, open-domain hallucinations are broad claims made that are less detectable (Walczak & Cellary, 2023). Hallucinations also appear more frequent when AI has to contend with controversial topics or topics where limited data is available (Waldo & Boussard, 2025).

It is therefore imperative for facts to be researched before accepting responses from AI-generated content as truth. For students, this is especially important as they are building skills needed for academic research. If false information is taken as fact during the process of learning, this could also lead to concepts being misunderstood, having a negative impact on students' performance and concomitant motivation. Researchers like Watanabe (2024) also critique AI for hindering students' ability to think critically and independently.

Importantly, within the context of South African higher education and efforts to decolonise curriculum, criticism which suggests that AI perpetuates Western biases and excludes marginalised communities from design and coding remains especially relevant (Muldoon & Wu, 2023). De Villiers-Botha (2024) adds further caution in this regard pertaining to misinformation emanating from Generative AI due to the statistical prominence of majority opinion, which can further marginalise minority viewpoints by presenting majority opinion as indisputable fact.

Thus, whilst the technology of AI is potentially beneficial, the associated challenges, which include pedagogical implications as highlighted by Castello-Sirvent et al. (2024), must be understood at a deeper level. This supports the need for this study to examine the Proof of Concept (PoC) in terms of both benefits and challenges for AI's ethical incorporation into teaching and learning practice within a local higher education institution.

In summary, the opportunity for AI to potentially transform higher education is evident. However, its effective implementation in South African higher education requires thoughtful strategies and careful consideration of local contexts. Table 2 presents a summary of the various challenges of AI use and barriers to its adoption, along with mitigation strategies that have emanated from the literature engaged with in this section.

Challenge/Barrier	Summary	Mitigation Strategy	Authors
Diversity	Diverse student academic preparedness, large class sizes, multilingualism, inadequate	Redefine curriculum that positions AI as a partner in learning. Adopt best practices from	Gokceaslan et al (2024); Funda & Piderit (2024); Jiang & Nakatani (2025); Moore & Lookadoo, (2024);

	curriculum design, and variation in academic ability pose both a challenge and barrier. Diversity in student preparedness is another factor due to awareness and access.	nations like Uganda and Ethiopia, where AI adoption has shown success within the African context. Identify and assist students without access to adequate resources. Train students on the use of AI tools and provide inclusive support.	De Villiers-Botha (2024)
Absence or inadequate regulatory framework	Lack of policies or inadequate policies creates confusion, jeopardises AI's ethical use, increases the potential for security risks, compromises academic integrity and hinders students' ability to produce authentic work and develop critical thinking.	Implement robust regulatory frameworks with effective policies and guidelines for students' use of AI, aligned to faculty goals and learning outcomes. Include access and privacy protocols to safeguard students' data. Transparent guidelines reduce confusion, promote equitable access, and shift the focus from performance to meaningful learning. A phased approach of policy implementation, with ongoing legislative updates and monitoring initiatives is encouraged.	Naidoo and Pillay (2018); Hazari (2024), De Villiers-Botha (2024); (Moore & Lookadoo, 2024); Evangelista (2025); (Ivanov, 2023); Dube (2025)
Inertia/Avoidance	Lack of teaching experience and lecturer apathy, lack of institutional support, and	Effective policies, user-friendly designs, and pedagogical alignment can	Moore & Lookadoo (2024); Funda & Piderit (2024);

	socio-cultural context of the university result in lecturers' and institutions' reluctance to embrace AI integration. The negative aspects of AI use are given primacy over than the benefits, leading to negative perceptions and avoidance or resistance of AI integration in higher education.	overcome fear of change and apathy.	Gokceaslan et al (2024); Holmes et al (2021); Patel and Ragolane (2024); Ivanov (2023)
Pedagogical challenges	Lecturers' lack of exposure and training to use AI tools in pedagogy hinder adoption of AI in practice. Misalignment of curricula with technology advancements and industry needs, along with passive teaching and learning strategies present barriers to AI's effective integration in higher education.	Shift from passive to active teaching and learning strategies. Embed AI into curriculum.	Ballantine et al. (2024), Eze et al. (2022)
Data privacy and security	Lack of safeguards can lead to data leakage, data misuse, algorithmic bias and invasive methods, such as proctoring.	Implement rigorous data governance frameworks and remain transparent regarding what data is being collected, how it is to be used and shared. Institute regular policy reviews and	Xia et al (2024), Xue et al (2025), Yang & Beil (2024)

		updates, as well as ongoing training to ensure that data remains secure.	
Hallucinations	AI tends to hallucinate when engaging with controversial topics or topics where limited data is available resulting in misinformation.	Train students to review AI generated content to establish the facts. Teach students to think critically and independently.	Bubeck et al (2023), Walczak & Cellary, (2023), Waldo & Boussard, (2025), Watanabe (2024)
Bias and discrimination	AI is criticised for perpetuating Western biases by excluding marginalised communities from design and coding. The statistical prominence of majority opinion in AI generated content can further marginalise minority viewpoints by presenting majority opinion as indisputable fact.	Validate AI tools to eliminate bias, ensuring the data is representative of diverse social and cultural backgrounds. Train AI tools in multiple languages to support multilingual usage and reduce dominant cultural bias. Create AI content to include local perspectives.	(Muldoon & Wu, 2023), De Villiers-Botha (2024)

Table 2: Summary of the challenges and barriers to AI integration in higher education, along with mitigation strategies (Author collation)

This study contributes to this existing body of knowledge on AI in education by exploring the experiences of students with a customised Generative AI tool, providing insights into the challenges, readiness factors, and pedagogical impacts that must be addressed to ensure successful adoption of Generative AI in higher education.

2.7 Generative AI in Accounting Education

Accounting is widely recognised as a global discipline requiring standardisation and alignment with evolving industry practices (Muller, 2025). However, Accounting education has been criticised for its overemphasis on technical content and outdated pedagogical approaches that fail to reflect current industry demands (Ballantine et al., 2024).

Technological and professional transformations across Accounting fields, including auditing, taxation, and forensic accounting, have shifted the skills required of graduates. Beyond technical competence, there is increasing emphasis on critical thinking, ethical awareness, and conceptual understanding (Rao & Maddeni, 2024; Sorensen & Tuberville, 2025; Sangster, 2022). This necessitates curriculum reform and the adoption of innovative pedagogical strategies.

Whilst universities are faced with the demand for curriculum reform, they also need to navigate challenges within their own contexts. In Australia, the challenges facing Accounting education include an increase in international enrolments, high student-to-staff ratios, lack of funding, an aged academic fraternity, and curriculum which does not meet industry needs (De Lange & Watty, 2011). In India, challenges include the absence of practical components in Accounting education, insufficiently trained lecturers, lack of technology integration, and a misalignment with industry and students' expectations (Rao & Maddeni, 2024). Similarly, a study in Saudi Arabia established a gap between Accounting curriculum and industry needs (Alsughayer & Alsultan, 2023). In Libya, where the Accounting profession is founded upon British and American standards, the industry and curriculum gap is once again highlighted, along with other challenges such as the lack of qualified and trained academics (Ahmad & Gao, 2004).

First-year Accounting students in South African universities face persistent challenges in mastering foundational concepts (Makhathini et al., 2024). Calma (2020) asserts that the intensity of Accounting coursework is overwhelming for students and requires self-directed study and preparation (Baard et al., 2025). The underdevelopment of such skills, including numeracy skills at secondary level (Baard et al., 2025), and problems related to conceptualisation (Olifant et al., 2024) are some of the main contributing factors to the learning challenges students encounter in first-year Accounting modules. This has a domino effect, contributing to high dropout rates, extended graduation timelines, and limited employability which characterise Accounting degrees (Makhathini et al., 2024).

Research indicates that these struggles are often due to a combination of cognitive, linguistic, and structural barriers. Specifically, underdeveloped analytical and problem-solving skills, difficulty in understanding abstract Accounting principles, and the

challenge of engaging with English as the primary medium of instruction are prevalent (Parker & van Rooyen, 2024). Furthermore, the continued reliance on traditional pedagogical approaches such as passive instructional methods and rote learning has been shown to be insufficient in developing critical thinking and deep conceptual understanding (Eze et al., 2022). To overcome these challenges, Olifant et al. (2024) advocate for a fundamental shift of the current teaching approach encouraging active student engagement and incorporating exposure to practical application in Accounting education.

Moreover, in a study by De Villiers and Farrington (2017) motivated by the poor pass rates in Accounting, particularly at first-year level, the authors recommend providing students with opportunities to identify and summarise unfamiliar Accounting terminology and to complete online self-assessments to support mastery of learning outcomes. This directly supports the need for this study to explore how AI-generated lecture summaries and pathway questions shape students' learning in a first-year Accounting module. Given the role of Accounting as a scarce and essential skill in the country, the quality of Accounting education and the concomitant understanding of students' learning experiences and academic performance is vital to the country's economic and social development (Parker & Van Rooyen, 2024).

The increasing integration of AI tools in higher education offers opportunities to address challenges in Accounting education by alleviating cognitive barriers and improving students' grasp of complex module concepts (De Villiers-Botha, 2024; Patel & Ragolane, 2024; Ballentine et al., 2024). Examples of such AI tools include the AE Bot incorporated within teaching and learning practice at Pretoria University and Shakai, that can support students to clarify concepts in Accounting (Coetzee, 2024; Shakai, 2025).

However, evidence from AI implementation studies reveals that integration challenges may limit realisation of these potential benefits. Studies document theory-practice gaps where AI supports conceptual understanding but inadequately develops procedural competence (Landsberg & van den Berg, 2023), usability barriers that prevent sustained engagement regardless of content quality (Moore & Lookadoo, 2024), and conditional effectiveness patterns where benefits materialise only under specific circumstances for particular learner subgroups (Selwyn, 2019). These findings

suggest that AI integration requires careful pedagogical design addressing implementation challenges rather than simple technology deployment assuming that AI capabilities automatically translate into learning benefits.

While studies have demonstrated potential benefits of AI in education (Luckin et al., 2016; Holmes, Bialik & Fadel, 2019), research into its application within South African Accounting education remains sparse (Zawacki-Richter et al., 2019). This justifies the study's aim to explore the role of Generative AI in supporting first-year Accounting students in South African higher education. Specifically, exploring how AI-driven interventions can facilitate cognitive engagement, support self-directed learning, and enhance conceptual mastery in Accounting. Moreover, the study examines potential challenges in AI-mediated learning environments (Selwyn, 2019). This research study therefore provides empirical insights into the benefits and limitations of AI in enhancing learning outcomes for South African first-year Accounting students, contributing to the broader discourse on digital transformation in higher education.

2.8 Conclusion

This chapter established the theoretical and empirical foundation for investigating first-year Accounting students' learning experiences with customised Generative AI resources. The theoretical framework integrating Self-Directed Learning theory, Technology Acceptance Model, and constructivist principles provides a multidimensional analytical lens for examining adoption patterns, learning processes, and pedagogical appropriateness. SDL theory illuminates how technology supports or constrains learner autonomy through its effects on self-management, self-monitoring, and motivation. TAM explains adoption through perceived usefulness and ease of use, with task-technology fit mediating these relationships. Constructivism provides criteria for evaluating whether AI supports authentic learning through active knowledge construction or operates primarily as information delivery mechanism.

Literature review revealed that while AI offers potential benefits in higher education, personalised learning, immediate feedback, flexible access, conceptual clarification, evidence suggests effectiveness is conditional, depending on implementation quality, pedagogical design, and contextual factors. International and South African research documents high AI adoption rates among students and predominantly positive perceptions of usefulness. However, most studies rely on self-report measures of

perceived benefits rather than objective assessment of actual learning outcomes, representing a significant gap in current knowledge base.

Furthermore, substantial literature documents implementation challenges constraining AI effectiveness even when technology capabilities are sophisticated. These challenges include diversity in student academic preparedness and AI literacy creating equity concerns; absence or inadequacy of policy frameworks governing ethical use and academic integrity; institutional and faculty inertia resisting pedagogical innovation; data privacy and security concerns requiring robust governance; AI hallucinations and biases necessitating critical evaluation; and pedagogical misalignments where AI capabilities don't match learning task requirements. Mitigation strategies exist for each challenge, but implementation requires thoughtful planning, resource investment, and sustained institutional commitment.

Within Accounting education specifically, literature reveals persistent calls for curriculum reform addressing theory-practice gaps, integrating technology meaningfully, developing critical thinking beyond technical competency, and preparing graduates for AI-integrated workplaces. Professional Accounting roles are transforming through automation of routine tasks, shifting emphasis toward analytical interpretation, ethical judgment, and strategic thinking. Accounting education must evolve correspondingly, though evidence regarding how to achieve such evolution through AI integration remains limited, particularly in South African contexts.

This study addresses multiple gaps in existing literature. First, it examines AI implementation in South African Accounting education, an underrepresented context in international literature, providing evidence of whether patterns documented globally transfer to resource-constrained contexts marked by diverse student preparedness. Second, it employs mixed-methods design integrating quantitative adoption patterns with qualitative explanations of mechanisms underlying these patterns, moving beyond self-report surveys toward deeper understanding. Third, it investigates conditional effectiveness by examining when, why, and for whom AI supports learning effectively rather than assuming uniform effects. Fourth, it applies and evaluates SDL and TAM theoretical frameworks in professional education context where theory originated in different settings, examining whether theoretical predictions hold or require refinement.

The investigation recognises that AI's role in Accounting education depends not on technology capabilities alone but on pedagogical integration quality, alignment with assessment demands, usability supporting sustained engagement, and careful attention to equity implications. Enthusiastic technology adoption without addressing these factors risks disappointing outcomes despite substantial investment. Conversely, thoughtfully designed AI integration addressing documented implementation challenges may realise potential benefits for student learning, particularly in contexts like South Africa where large classes and diverse preparedness create pedagogical challenges that well-designed technology might help address.

Ultimately, universities face strategic decisions about AI integration requiring evidence-based guidance balancing potential benefits against implementation challenges. Those choosing integration must leverage AI capabilities through curricula encouraging critical thinking, policies ensuring ethical use, faculty development supporting pedagogical innovation, and attention to equity ensuring that AI narrows rather than widens educational opportunity gaps. Simplistic narratives positioning AI as either silver bullet or existential threat prove unhelpful; nuanced understanding of conditional effectiveness under varying circumstances provides more useful foundation for decision-making.

Chapter 3 details the mixed-methods research design employed to investigate these questions empirically, examining both potential benefits and documented challenges within the specific context of first-year Accounting education at Emeritus College. The explanatory sequential design enables initial quantitative mapping of adoption patterns and perceptions across the full cohort, followed by qualitative exploration of mechanisms, contextual factors, and conditional effectiveness patterns through interviews and focus groups. This methodological approach addresses literature gaps by moving beyond perception measurement toward understanding of why certain patterns emerge and what factors mediate effectiveness.

Chapter 3: Research Methodology and Design

3.1 Introduction

The purpose of this chapter is to provide a detailed account of the research methods employed in this case study. Based on the study being exploratory in nature, illuminating findings within an area of research with limited understanding, the design has remained flexible throughout the data collection and analysis phases (du Plooy-Cilliers et al., 2021). However, whilst remaining flexible, careful consideration has been given to the research methods selected. A combination of positivist and interpretivist approaches afforded through the technique of mixed-method research enables a thorough examination of the phenomenon under study. Justification for the mixed-method approach and the associated techniques are expounded upon within this chapter.

This chapter proceeds systematically by first establishing the research paradigm grounding the investigation (Section 3.2), then detailing the mixed-methods case study design (Section 3.3), describing sampling strategies and participant characteristics (Section 3.4), explaining data generation methods (Section 3.4.2), outlining analytical approaches (Section 3.5), addressing ethical considerations (Section 3.6), establishing validity and reliability criteria (Section 3.7), acknowledging methodological limitations (Section 3.8), and concluding with synthesis (Section 3.9).

3.2 Research Paradigm

A paradigm is a tradition which informs the theoretical and conceptual framework for a research study, grouping theories according to the philosophical assumptions and research methodology (du Plooy-Cilliers et al., 2021). According to Kaushik and Walsh (2019), paradigms support the researcher to solve the research problem.

3.2.1 Pragmatism

The pragmatist paradigm is concerned with the nature of experiences and therefore focuses on the consequences of the research and research question, rather than on the methods (Kaushik & Walsh, 2019). The paradigm therefore affords equal status to quantitative and qualitative components of the study (Schoonenboom & Johnson, 2017). The combination of positivist and interpretive philosophical frameworks, in alignment with the pragmatic paradigm, mitigated the limitations of purely positivist or interpretivist approaches through a dynamic interplay between theory and practice (Greene, 2009).

Pragmatism as a philosophy is underpinned by the notion that all knowledge and reality are based on beliefs and habits which are socially constructed (Kaushik & Walsh, 2019). As the pragmatic approach focuses on the nature of experience and is deemed contextual, this paradigm was established as appropriate for this study, which has explored the nuanced experiences of first-year Accounting students' engagement with a Generative AI tool in their learning process. According to Creswell (2009), pragmatism is a sufficient foundation for parallel designs (Gobo, 2023). The pragmatic approach supported the generation of practical and contextual knowledge through the study, as well as the study's aim to provide actionable, viable, and relevant knowledge in relation to the research problem (Elgeddawy & Abouraia, 2024).

The paradigm therefore enabled a pragmatic or realist perspective, whilst also considering the sociocultural, interpretive, and contextual perspective (Greene, 2008). The pragmatic approach rendered flexibility and openness to the study, supporting the interpretation of data across the quantitative and qualitative phases of the study, acknowledging that the constructed quantitative understanding could not be isolated from the constructed qualitative understanding (Elgeddawy & Abouraia, 2024).

3.3 Research Design

According to du Plooy-Cilliers et al. (2021), the design of a research study is guided by specific aims within a philosophical and theoretical framework that informs the methodological orientation of the study (i.e., sampling, data collection, and analysis strategies). This study incorporated a mixed design and adopted a pragmatic approach to understand students' perspectives of how a customised Generative AI tool shaped their learning experiences within a first-year Accounting module at a private higher education institution.

3.3.1 Mixed-Methods Approach

The design of this case study is underpinned by Teddlie and Tashakkori's (2009) definition of mixed-methods research, enabled through the integration of quantitative and qualitative data which has derived a rich exploration, through both numerical and narrative perspectives, into how AI-generated resources shape students' engagement with the curriculum and how these resources shape their cognitive development and attitudes towards their learning of Accounting (Modell, 2011). The juxtaposition of quantitative and qualitative data has provided a complete and comprehensive

understanding of how AI tools shape students' learning in the ACC1A module, achieving the aim of the study (Creswell, 2004).

Hence this approach was identified as being the most appropriate, as neither quantitative nor qualitative data alone would have been sufficient to respond to the research question, limiting the study's findings. The mixed-methods approach has therefore addressed the study's objectives, purpose, and research questions (Collins & O'Cathain, 2009). A holistic view considering both perspectives, of those students who found benefit as well as those who did not, was achieved by triangulating findings from the quantitative and qualitative data gathered, linked through the analysis, thereby validating the results and enriching the study's outcomes (Sharma et al., 2023; Draucker, 2020).

3.3.1.1 Exploratory Case Study Design

An exploratory case study design, according to Yin (2003), is especially well-suited for examining phenomena in real-life settings, particularly when there is a dearth of prior knowledge or when the research seeks to investigate a complicated, context-bound problem (Baxter & Jack, 2008). This design allows researchers to gain insights into under-researched areas, often where variables and their interactions are not fully understood. The aim of this study was to explore how first-year Accounting students interact with and view the integration of an AI-driven learning tool in a South African university setting. The exploratory case study approach was therefore ideally suited to this aim. Given that AI tools in higher education are still emerging, especially in non-technical disciplines such as Accounting, this research provides an essential step toward understanding their educational implications from a pedagogical perspective (Zawacki-Richter et al., 2024).

Case study research is acknowledged for its methodological approach to offer a holistic understanding of a phenomenon, particularly when the distinctions between the phenomenon and its context are difficult to distinguish (Baxter & Jack, 2008). In an area that has not received enough attention, the exploratory case study is especially helpful when the researcher wants to uncover new information or establish the foundation for future research (Coombs, 2022). With an emphasis on the participants' interactions with the AI tool and the larger social, educational, and

technological contexts in which these interactions take place, this method enabled a thorough examination of the participants' experiences and perceptions.

The main advantage of the case study's approach was its focus on the contextual elements influencing the phenomenon being studied (Cleland, MacLeod & Ellaway, 2021). The context of this study encompassed the sociocultural dynamics of higher education in South Africa, the technological literacy of the students, and their past experiences with artificial intelligence and digital learning resources. By examining these contextual factors, the case study sought to understand how they influenced students' use of AI tools and provide more in-depth understanding of their educational journeys (Kreijns et al., 2020).

Moreover, acknowledging that AI tools in education are relatively new, the exploratory case study design allowed the research to explore emerging phenomena in depth, uncovering new dimensions of students' experiences with AI-driven learning tools. According to Zawacki-Richter et al. (2024), the predominance of current literature focuses on the individual level of students, instead of exploring the pedagogical dimension of their learning. Based on this identified gap in research, justification is established for a case study approach which afforded flexibility to respond to the emerging insights into students' experiences with AI-driven learning tools from a pedagogical perspective. Moreover, this afforded a more in-depth understanding of how AI influences students' academic self-efficacy, motivation, and learning outcomes within the South African higher education landscape.

In this study, the research questions focused on understanding how first-year Accounting students experienced and interacted with an AI tool integrated into their learning. By adopting an exploratory case study design, the study provided a deep dive into the nuances of these interactions. The exploratory case study enabled a wide range of student experiences to be captured, from those who were positive about the AI tool to those who encountered challenges. This depth of analysis was possible through the production of qualitative data from one-on-one interviews and focus groups (Coombs, 2022). The study was able to identify the personal and social factors that affected how students adopted and used the AI tool.

By focusing on first-year Accounting students at a South African university as the conceptual framework, this case study ensured that the findings are grounded in the

specific educational and sociocultural context of the region (Crowe et al., 2011). South Africa's higher education system faces unique challenges related to inequality, access to technology, and varying levels of digital literacy among students (Boughey & McKenna, 2020). Thus, the case study was designed to uncover how these factors influence students' perceptions and adoption of AI tools within this unique context.

3.3.1.2 Mixed-Methods Design – Explanatory Sequential

Greene (2009) affirms that the value of integrating quantitative and qualitative data lies in the mixing of results to yield deeper insight, supported by the philosophical assumptions and theoretical frameworks. Therefore, a robust study was afforded through the design which aligned to the explanatory sequential model of mixed-methods design, meaning that it followed an initial quantitative phase of data collection and analysis, followed by a second phase of qualitative data production and analysis to support the explanation of quantitative results and to advance the study's aims (Creswell, 2004).

Firstly, the design's integration of the two approaches incorporated the building approach, using the results of the quantitative data collection to guide the construction of the qualitative data collection instruments, which was used in the subsequent qualitative data collection phase (Draucker et al., 2020). The basis for constructing the qualitative instruments in this way was to provide an explanation for the results from the quantitative data analysis, by relating it to the contextual circumstances in which the quantitative outcomes were produced (Schoonenboom & Johnson, 2017).

Secondly, using the merging approach, the major quantitative and qualitative findings were identified to denote points of convergence and divergence of the study's data from the two approaches (Draucker et al., 2020). The justification for using this design, incorporating two levels of integration, was to achieve contextual understanding of the ACC1A students' learning experiences within the chosen population (Schoonenboom & Johnson, 2017).

3.4 Research Method

3.4.1 Sampling

The target population for the study comprised ACC1A students who were involved in the Proof of Concept at Emeritus College. Following the explanatory sequential design, there were two phases of sampling, the first sample for the quantitative phase

and the second sample for the qualitative phase. Both phases employed non-probability, purposive sampling. Non-probability, purposive sampling requires the selection of participants who are representative of the broader population (du Plooy-Cilliers et al., 2021). The justification for utilising purposive sampling in this study was to select participants that were best suited to provide responses to the research questions, deriving rich data (Patton, 2015, as cited in Miller et al., 2023).

To understand the diverse experiences that students had with AI-integrated learning tools, the study employed a maximum variation purposive sampling strategy, considering significant variables like student diversity with respect to race, gender, and socioeconomic background (Nyimbili & Nyimbili, 2024). This approach facilitated the identification of patterns and differences in how students interact with AI resources, based on their diverse backgrounds and prior learning experiences.

Quantitative Phase

The quantitative phase comprised a purposive sample of students enrolled in the ACC1A module at the Sandton, Durban North, Durban Westville, and Pietermaritzburg campuses. These four campuses were purposively selected based on institutional data indicating highest AI tool usage by lecturers, ensuring participants had substantial exposure to AI-generated resources necessary for meaningful responses to research questions. The quantitative data was collected through an online questionnaire distributed to 416 students between July and September 2025, yielding a 36% response rate ($n=149$). This response rate is acceptable for online surveys, which typically achieve 34-36% participation (Mursa et al., 2025). The questionnaire's reliability was confirmed through Cronbach's alpha ($\alpha = 0.87$), indicating strong internal consistency for the Likert-scale items measuring student perceptions.

The quantitative phase employed descriptive statistics to characterise student experiences and Spearman's rank correlation coefficients to examine relationships between variables. As an exploratory case study focused on understanding experiences rather than testing causal hypotheses, inferential statistics were not employed. The descriptive approach aligns with the study's interpretivist epistemology, which seeks to understand meaning rather than establish generalisable laws (Creswell & Poth, 2018).

Data derived from the quantitative phase guided the construction of the data generation instrument used in the qualitative phase. The responses to the cross-sectional questionnaire informed the questions for the semi-structured interview by highlighting areas that were probed at a deeper level.

Qualitative Phase

This qualitative phase employed an interpretivist epistemology, seeking to understand the subjective meanings students constructed from their experiences with AI resources (Creswell & Poth, 2018). Interpretivism assumes that reality is socially constructed and that multiple valid interpretations exist, requiring researchers to understand phenomena from participants' perspectives rather than imposing predetermined categories (Merriam & Tisdell, 2016). This epistemological stance aligns with the study's exploratory purpose to understand how students made sense of AI tools within their unique learning contexts rather than testing hypotheses about AI effectiveness.

The qualitative design employed two complementary data collection methods including semi-structured interviews and focus group discussions. Semi-structured interviews allowed exploration of individual experiences, learning strategies, and personal reactions to AI resources, providing depth and nuance (Brinkmann & Kvale, 2015). Focus group discussions facilitated peer interaction, enabling students to build on each other's observations, challenge or validate perspectives, and collectively construct meaning (Krueger & Casey, 2015). Together, these methods generated both individual narratives and socially negotiated understandings.

The qualitative phase comprised 24 participants. 14 students participated in semi-structured interviews, and 10 different students participated in focus group discussions. These were distinct groups with no overlap between interview and focus group participants, yielding 24 total unique qualitative participants. All participants were first-year Accounting students enrolled in the ACC1A module at the Pietermaritzburg campus.

Participants were selected through purposive sampling designed to capture variation in AI engagement levels identified in Chapter 4's quantitative analysis. Following Patton's (2015) maximum variation sampling strategy, students were sought representing high, moderate, and low AI usage patterns to understand how different

engagement intensities shaped learning experiences. This approach enabled comparison and depth, providing rich contrasting data of how students with varying levels of usage engaged with the tool, providing an evaluation of usage impact on learning experience. Practical constraints limited sampling to the Pietermaritzburg campus due to researcher access and resource availability during the September-October 2025 data collection period.

3.4.1.1 Inclusion Criteria for the Quantitative Phase

All 416 students registered for the ACC1A Module were invited to participate in the quantitative phase of the study. However, only 149 students participated.

3.4.1.2 Inclusion Criteria for Participants in the Qualitative Phase

The following inclusion criteria define the homogenous population that fulfilled the requirements of the research (Panacek & Thompson, 2007):

Academic Performance Stratification

The sampling strategy intended to recruit students across performance levels to examine whether AI effectiveness varied by prior achievement: top achievers (90th percentile or above, top 10% of the class), middle achievers (40-70th percentile), and low achievers (bottom 10% of the class). The intention was to include 6 students from each performance category, representing distinct achievement profiles. However, voluntary participation yielded unbalanced representation: 6 top achievers, 17 middle achievers, and only 1 low achiever.

This underrepresentation of struggling students is consistent with literature documenting that low-performing students exhibit lower engagement and motivation (Schnitzler et al., 2021), affecting voluntary study participation. Low-performing students are typically disengaged and exhibit low motivation (Schnitzler et al., 2021). Empirical studies, such as the one by Schnitzler et al. (2021), provide a plausible explanation for the underrepresentation of low academic performers within the final voluntary sample.

Minimum Participation Requirement

Students were required to have at least 75% attendance within the ACC1A module and to have completed the first-semester assessment. This ensured that students

selected for the study had sufficient engagement in the module to provide meaningful insights pertaining to their learning experience.

Usage Requirement

Students were selected based on high, moderate, and low AI tool usage to provide insights into the factors that influenced usage and how varying usage influenced learning experiences.

Voluntary Participation

Participation in the study was voluntary, and students were informed that their academic performance would not affect their standing or grades in the course. Students provided informed consent before participating in the study and acknowledged their understanding of the purpose of the study, the confidentiality of their responses, and their right to withdraw at any time without academic penalty.

Inclusion of Diverse Backgrounds

Efforts were made to ensure that the sample was representative of the student body in terms of gender, race, and socioeconomic background, to capture a broad spectrum of experiences across different demographic groups such that findings are applicable to a diverse student population.

3.4.1.3 Exclusion Criteria for Qualitative Phase

According to Panacek and Thompson (2007), exclusion criteria are as important as inclusion criteria to avoid poor quality data collection. In this study, students who had not met the minimum attendance requirement of 75% of the AI-integrated sessions during the first semester were excluded from the study, as they would have been unable to afford the necessary insights required to answer the research questions.

3.4.1.4 Biographical Information

Quantitative Phase

Demographic characteristics revealed a respondent profile of predominantly young (18-24 years), technologically experienced (90% prior AI use), relatively balanced by gender (56% male, 41% female), distributed across Durban Westville (44.3%, n=66),

Sandton (24.8%, n=37), Durban North (24.2%, n=36), and Pietermaritzburg (6.7%, n=10), reflecting varied socioeconomic contexts.

Qualitative Phase

Table 3 below describes the demographic characteristics of the qualitative sample. Analytical implications of the sample characteristics are discussed in Chapter 5.

Demographic category	Semi-structured interviews (n=14)	Focus groups (n=10)	Total Qualitative Sample (n=24)
Male	6 (42.9%)	3 (30%)	9 (37.5%)
Female	8 (57.1%)	7 (70%)	15 (62.5%)
African	9 (64.3%)	5 (50%)	14 (58.3%)
Indian	2 (14.3%)	3 (30%)	5 (20.8%)
Coloured	1 (7.1%)	1 (10%)	2 (8.3%)
White	2 (14.3%)	1 (10%)	3 (12.5%)
Campus (Pietermaritzburg)	14 (100%)	10 (100%)	24 (100%)
Age range	18-21 years	18-21 years	18-21 years

Table 3: Demographic characteristics of the qualitative sample

3.4.2 Data Generation

3.4.2.1 Quantitative Data Generation

A cross-sectional questionnaire, including 5-point Likert-type (Part A of the questionnaire) and open-ended questions (Part B of the questionnaire), was used to generate data for the quantitative component of the study. The justification of the design of the questionnaire was to provide an overall, preliminary perspective of the phenomenon under study, with the aim of uncovering insights into students' learning experiences from a larger representative population comprising ACC1A students across multiple campuses actively involved in the PoC, at the end of the first semester (du Plooy-Cilliers et al., 2021).

This data generation method was framed by Self-Directed Learning (SDL) and Technology Acceptance Model (TAM) frameworks within a constructivist

understanding of learning. Questionnaire items examined how students perceived AI's support for autonomous learning dimensions identified by SDL theory (self-management, self-monitoring, and motivation), technology adoption patterns explained by TAM (perceived usefulness and ease of use), and how students actively constructed meaning from their interactions with AI-generated resources (constructivism). Cronbach's Alpha was used to find the correlation (internal consistency) between the answers to the 5-Point Likert-type questions (Part A), confirming which questions measured the same variable (e.g., perceived usefulness) (Olaniyi, 2019). This ensured the reliability of this data generation instrument (Olaniyi, 2019).

3.4.2.2 Qualitative Data Generation

The data generation for the qualitative component of the study comprised semi-structured interviews and focus group activities with students at the Pietermaritzburg campus.

Semi-Structured Interviews

Semi-structured interviews were conducted with 14 students during September 2025. Participants were recruited through ACC1A course announcements and direct invitations to students representing varied quantitative questionnaire responses (strongly agree, neutral, and disagree patterns). Interviews were conducted face-to-face in private campus venues, lasting 15-20 minutes each. The semi-structured interviews comprised a framework of themes guided by the quantitative component, explored in an informal, face-to-face interview (Ruslin et al., 2022).

Informed by SDL and TAM frameworks within a constructivist epistemology, the interviews explored students' reflective processes and self-regulation in relation to their learning experiences with the AI tool (SDL dimensions), technology adoption patterns including perceived usefulness and ease of use (TAM constructs), and how students actively constructed understanding from AI-mediated learning experiences (constructivism). Whilst the protocol provided structure, a flexible approach was adopted, allowing students to elaborate on experiences most salient to them and pursuing emergent themes through follow-up probing (Brinkmann & Kvale, 2015). Justification for this method was based on its ability to obtain a deeper comprehension

of individual student experiences, ensuring that relevant contexts were illuminated, and situational knowledge was produced (Ruslin et al., 2022).

Focus Group Discussions

Focus group discussions involved 10 students organised into four groups during two separate sessions in October 2025. Group sizes ranged from 2-3 participants, smaller than conventional focus group recommendations of 6-10 participants (Krueger & Casey, 2015). This deviation was deliberate. Smaller groups facilitated deeper individual contributions and ensured all voices were heard, particularly important given potential power dynamics among first-year students.

A constructivist approach was utilised during the focus group engagements to explore contextual factors such as how students interact with peers and AI-generated content, fostering collective knowledge construction in the context of the ACC1A module. Each two-hour session incorporated both structured discussion prompts and a set of four collaborative activities requiring students to analyse AI-generated resources and reflect on learning processes.

The first activity comprised an exploration into how participants connected AI-generated lecture summaries to their understanding of learning outcomes within the ACC1A module. This reflective activity drew on learning units 3 and 4 which focused on VAT and the General Ledger. Students reflected and discussed how the AI-generated summaries supported their understanding of these Accounting concepts and how students connected their understanding to application-type questions through an example provided. Finally in this activity, students created concept maps to show how the AI-generated summaries helped them or created barriers to understand content, link ideas, and develop skills.

In the second activity, referred to as critical incidents reflections, students discussed and noted specific incidents when the AI tool either enhanced or impeded understanding or skills development. Drawing on the first two activities, the third activity and discussion focused on ranking and justifying skills to evaluate the perceived impact of the AI tool on different types of skill development. In the fourth and final activity, students completed a comparative analysis between the textbook and the AI-generated summaries provided, distinguishing between the differences, similarities, and overlapping characteristics (in terms of the clarity of explanation, depth of

understanding, and usefulness for skill development) depicted in a Venn diagram. These activities generated written artefacts (annotated summaries, benefit-challenge charts) supplementing verbal discussions.

Justification for the focus group data generation method resides in its value to derive important data from spontaneous responses acquired through social interaction amongst the group, and its ability to achieve data saturation through multiple focus groups (Onwuegbuzi et al., 2009). All interviews and focus group discussions were audio-recorded with participant consent and transcribed verbatim.

Data generated from both methods was integrated, denoting critical points of convergence and divergence, affording a comprehensive and complete understanding of students' experiences of learning using Generative AI in the ACC1A module (Draucker et al., 2020).

3.5 Data Analysis

Aligned to the explanatory sequential design of the study, data analysis of the quantitative data preceded the analysis of qualitative data (Draucker et al., 2020). Various data analysis methods were used in this study, outlined in the following subsections.

3.5.1 Descriptive Statistics

Descriptive statistics were employed to analyse quantitative data (cross-sectional questionnaire, specifically Part A, 5-Point Likert-type questions). Data was analysed for modes, medians, and frequencies to describe the categorical variables. Spearman's rank correlation coefficients were used to assess whether there were statistically significant associations between the Likert-scale statements due to the ordinal nature of the variables. The relationship between many of the factors were shown to be statistically significant and positive. Once the relationships were assessed for statistical significance and direction, the strength of the relationship was assessed.

Crosstabulations were performed on various combinations of specific variables. To interpret the crosstabulations, the Pearson's Chi-square test of independence was used to establish significant associations, counts and frequencies were reviewed to identify common patterns, and Cramer's V was used to establish the effect size or strength of the association (Boone & Boone, 2012). Descriptive statistics quantified

perceptions, correlation analyses identified significant relationships, and statistical tests validated patterns.

3.5.2 Content Analysis of Qualitative Data

Content analysis was applied to qualitative data from open-ended questionnaire responses (Part B) and focus group activities using systematic coding procedures. Responses were read multiple times to identify manifest content (explicit statements) and latent content (underlying meanings). Categories were developed inductively from the data while also informed by SDL and TAM constructs, enabling both data-driven discovery and theory-informed interpretation. The justification for this method of analysis resided in its value to provide a systematic approach to summarising large volumes of textual data, adding depth and context to the data-driven narrative of students' learning experiences using a customised Generative AI tool in ACC1A (Rouder et al., 2021).

3.5.3 Thematic Analysis of Qualitative Data

Thematic analysis of semi-structured interview transcripts followed Braun and Clarke's (2006) six-phase approach of familiarisation through repeated reading, generating initial codes, searching for themes, reviewing themes, defining and naming themes, and producing the report. Data was colour-coded to track themes and relationships, with constant comparison ensuring thematic consistency (Annamalah, 2024). The analysis aimed to identify patterns in how students experienced AI-mediated learning, moving beyond surface descriptions to interpret underlying meanings. Aligned to the interpretive aim of the qualitative phase of the study's design, the justification for this method of analysis was to afford a more insightful comprehension of how and why students experienced certain learning outcomes in the ACC1A module.

3.5.4 Inductive and Deductive Coding

The responses from open-ended questions and reflections from the focus group activities were coded inductively and deductively to illuminate patterns and connections within the data (Rouder et al., 2021). Inductive coding allowed themes to emerge from the data itself, while deductive coding applied theoretical constructs from SDL, TAM, and constructivism to interpret student experiences. This combined approach ensured both discovery of unexpected patterns and theoretical grounding of interpretations. Justification for this method of analysis resided in its value to provide a systematic approach to summarising large volumes of textual data, adding depth

and context to the data-driven narrative of students' learning experiences using a customised Generative AI tool in ACC1A (Rouder et al., 2021).

3.5.5 Descriptive Coding for Conceptual and Skills Identification

Descriptive coding of qualitative evidence from focus group activities enabled identification of concepts and skills students reported developing or struggling with. Descriptive codes were assigned to responses focusing on explicit statements about learning outcomes, competency development, and barriers encountered (Stewart, 2025).

3.5.6 Qualitative Comparative Analysis

Qualitative comparative analysis of quantitative and qualitative data afforded practical and contextual understanding of the comparison between quantitative patterns and qualitative explanations. The justification for the use of this method lay in its ability to provide insights into the influencing factors of the phenomenon (Sherif et al., 2022). This integration enabled identification of convergence (where qualitative findings explained quantitative patterns) and divergence (where qualitative findings revealed complexities not captured quantitatively).

3.5.7 Summary of Data Analysis Strategies

Data analysis strategies employed in the study are summarised in Table 4, which provides a tabulated representation of the study's design aligned to the research questions and theoretical framework.

Research Question/ Objectives	Data Source	Data Generation Method	Theoretical Framework	Data Analysis Process
1. What are first-year students' learning experiences of engaging with AI-generated lecture summaries and pathway questions in the ACC1A module?	-First year ACC1A students	- Cross-sectional questionnaire	SDL and TAM	- Cronbach's Alpha to test the reliability of the instrument - Descriptive statistics of Likert Scale responses -Content Analysis of Open-ended responses
2. How does the customised Gen. AI tool shape first-year students' understanding of learning outcomes and skill development in the ACC1A module?	-First year ACC1A students	-Semi-structured interviews -Focus group activity	SDL and TAM	-Thematic analysis -Content analysis of reflections -Descriptive coding for evidence of conceptual understanding and skills development
3. Why do first-year students perceive the AI-generated resources as beneficial or challenging in supporting their learning in the ACC1A module?	-First year ACC1A students	-Semi-structured interviews - Focus Group Activities	SDL and TAM	-Thematic analysis -Comparative analysis of quantitative and qualitative data

Table 4: Data analysis methods (Author collation)

3.6 Ethical Considerations

This research received ethical clearance from Emeritus College's Research Ethics Committee (Protocol R.16016 [RPGS04]) and the University of KwaZulu-Natal (Protocol HSSREC/00009041/2025). All participants provided written informed consent after receiving information sheets explaining the study's purpose, procedures, risks, and benefits. Participation was entirely voluntary, with no influence on academic grades or course standing.

Within the qualitative phase, the principles of trustworthiness, credibility, dependability, and confirmability of the qualitative data were maintained (Amankwaa, 2016). Power dynamics within the qualitative phase of data collection were mitigated through transparent engagement with participants, emphasising my role as the researcher, or the outsider seeking to gather information (Darwin Holmes, 2020). Establishing this relationship with the participants ensured that the participants felt free to share their experiences, allowing the voices of the students to be authentically presented (McDonald, 2021).

Within the quantitative phase, ethical considerations included accuracy, integrity, and responsible handling of the quantitative data (Jones, 2000). Data integrity was maintained by avoiding falsification, distortion, or misuse of results (du Plooy-Cilliers et al., 2021). For both phases, an informed consent form was issued to those invited to participate in the study (including the project title, details of the researcher and supervisor, project aim and objectives, overview of the study, participant involvement, confidentiality, anonymity, and data storage) (Chowdhury & Shil, 2021). Participant confidentiality was strictly adhered to, aligning with ethical guidelines that emphasise respect and beneficence (Cooper & McNair, 2015). These ethical controls ensured that participants were protected from potential harm, and the responsible and ethical execution of the study.

Confidentiality was maintained through pseudonymisation and secure data storage. Audio recordings and transcripts were stored in password-protected files accessible only to me and my research supervisor. Data will be destroyed five years after study completion per institutional policy.

Power dynamics between researcher and student participants required careful navigation. To minimise potential coercion, recruitment was conducted through

general course announcements rather than direct approaches, allowing students to volunteer rather than feeling pressured to participate. I explicitly stated that critical feedback was valuable and would not be penalised, and interview questions avoided leading or suggestive phrasing.

3.7 Validity and Reliability

The combination of interpretivist and positivist paradigms mitigated the limitations of purely positivist or interpretivist approaches through a dynamic interplay between theory and practice (Greene, 2009). Limitations pertaining to mixing qualitative and quantitative methods were mitigated through the legitimacy of convergent and divergent evidence to strengthen the findings and deepen the understanding of how AI tools impact students' engagement and learning experience in the ACC1A module (Collins & O'Cathain, 2009).

To ensure the validity of the quantitative approach, the criteria of internal validity, external validity, reliability, and objectivity were applied (du Plooy-Cilliers et al., 2021). Moreover, Cronbach's Alpha was used to ensure reliability of Part A of the cross-sectional questionnaire (Olaniyi, 2019). According to Patten (2002), as cited in Chowdhury and Shil (2021), validity and reliability for robust qualitative methods are dependent on naturalistic inquiry, inductive analysis, and holistic thinking. These criteria were met by the study by ensuring that it took place in Emeritus College's natural environment, that the research methodology and qualitative case study design described in the preceding sections were sound, and that enough time was spent in the field gathering data to minimise bias.

Moreover, the principles pertaining to the value of truth, applicability, consistency, and neutrality were maintained in the study (Lorenzini et al., 2024). Construct validity was achieved by triangulating the multiple data sources from the cross-sectional questionnaire, semi-structured interviews, and focus group questions (Yazan, 2015). To ensure quality in the analysis of data, the process from raw data to results was made transparent in a tabulated format (Bengtsson, 2016). In addition, participants were given an opportunity to review their transcribed responses to ensure respondent validation (Bengtsson, 2016). The justification of the design which supports the quality of inferences, along with the sampling and analysis method which supports

legitimation, presented a validation and quality framework for a robust study (Lorenzini et al., 2024).

Qualitative research was evaluated through criteria distinct from quantitative validity and reliability (Lincoln & Guba, 1985). I employed multiple strategies to enhance trustworthiness:

Credibility (Internal Validity)

Prolonged engagement with data through multiple readings, iterative coding, and constant comparison ensured interpretations were grounded in evidence rather than imposed assumptions. Member checking was conducted informally: when analysing focus group data, I verified emergent interpretations with participants during the sessions, asking "Am I understanding correctly that...?" to confirm or refine interpretations.

Transferability (External Validity)

Thick description of context, participants, and procedures (provided in this chapter) enables readers to assess whether findings apply to their contexts. I explicitly acknowledge limitations (single-campus sampling, gender imbalance, small sample size) that constrain transferability.

Dependability (Reliability)

I maintained an audit trail documenting coding decisions, theme development, and analytical revisions. This trail includes dated reflective memos explaining why certain interpretive choices were made, enabling transparency about the analytical process.

Confirmability (Objectivity)

Recognising that complete objectivity is impossible in interpretivist research, I practiced reflexivity by acknowledging my positionality and potential biases. As both researcher and educator at Emeritus College, I hold positive views about technology-enhanced learning, which could bias interpretations toward favourable AI assessments. To counter this, I deliberately sought disconfirming evidence, paying particular attention to students expressing neutral or negative experiences and challenging my own assumptions when coding critical feedback.

3.8 Methodological Limitations of the Study

Limitations of Quantitative Findings

Several methodological constraints limit interpretation:

Self-Report Bias

All data derived from student perceptions via the questionnaire. Students may have provided socially desirable responses or lacked accurate metacognitive awareness to judge whether learning improved. Actual learning outcomes, comparing grades or competency assessments between AI users and non-users, were not measured, preventing causal claims about AI effectiveness beyond perceived usefulness.

Cross-Sectional Design

Data represent a single time point following eight weeks of AI tool usage. This design precludes causal inference, meaning we cannot conclude AI tools caused learning benefits. Students experiencing benefits may have been predisposed through prior AI familiarity, higher digital literacy, or stronger intrinsic motivation. Longitudinal or experimental designs would strengthen causal inference by tracking perception changes over time or comparing randomly assigned groups.

No Control Group

Without comparison group learning without AI tools, we cannot isolate AI effects from other pedagogical factors, such as instructor quality, curriculum design, peer support, personal study habits. The AI tool operated within complex learning ecology; attributing outcomes solely to AI oversimplifies. Ideally, controlled experiments comparing matched sections with and without AI would clarify unique contributions.

Missing Subgroup Analyses

Sample size constraints (n=149) prevented robust subgroup comparisons by gender, campus, prior AI experience, or academic performance. These analyses might reveal differential effectiveness. Perhaps male and female students valued different AI features; perhaps high-performing students leveraged AI differently than struggling students; perhaps prior AI experience moderated perceptions (though 89.9% had experience, limiting variance). These remain important questions warranting larger-sample research.

Quantitative-Qualitative Gap

Numbers reveal what students perceived but not why. The 40-47% neutral responses are statistically meaningful but substantively opaque; we don't know what "neutral" meant to respondents. Did they feel genuinely ambivalent? Were benefits conditional? Did they lack comparison points? Qualitative inquiry addresses this interpretive gap.

Measurement Limitations

Likert-scale items, while efficient for quantifying perceptions, constrain responses to predetermined categories. Students may have held opinions not captured by item wording. For instance, no items explicitly asked about SDL dimensions (self-management, self-monitoring, motivation), requiring indirect inference from constructs like engagement and confidence.

Limitations of Qualitative Findings

Several methodological constraints limit interpretation:

Sample Size and Saturation

With 24 total participants (14 interviews, 10 focus group participants), thematic saturation may not have been fully achieved. While major themes became evident after approximately 10 interviews, subtler patterns or minority experiences may have been missed. Ideally, sampling would have continued until no new themes emerged, but time and resource constraints necessitated stopping at 24 participants.

Single-Campus Limitation

The exclusive focus on Pietermaritzburg campus is the most significant limitation. Student experiences at Sandton, Durban Westville, or Durban North campuses may differ substantially due to infrastructure quality, socioeconomic contexts, and prior technology exposure. Findings may not transfer to urban, resource-rich settings.

Retrospective Self-Report

Interviews were conducted in September 2025, and focus groups in October 2025, weeks after students completed the eight-week AI intervention. This temporal distance means students reconstructed experiences from memory, potentially distorting details, emphasising memorable episodes while forgetting routine interactions, or rationalising

experiences in hindsight. Concurrent data collection (for example, learning journals maintained during AI tool usage) would have provided more accurate accounts but was not feasible.

Researcher Positionality

My role as the head of campus at Emeritus College, investigating an institutionally implemented AI tool, created potential bias toward favourable interpretations. While I practiced reflexivity and sought disconfirming evidence, my embeddedness in the institutional context may have limited critical distance. An external researcher might have generated different interpretations.

3.9 Conclusion

This chapter presented a comprehensive overview of the research methodology employed in this study. The research paradigm and study's design have been suitably discussed and justified in alignment with the study's purpose and research aims. The concomitant decisions pertaining to purposive sampling, to the data generation and analysis methods for this exploratory case study have ensured that the combination of positivist and interpretive philosophical frameworks, in alignment with the pragmatic paradigm, mitigated the limitations of purely positivist or interpretivist approaches through a dynamic interplay between theory and practice (Greene, 2009).

The chapter established that the explanatory sequential mixed-methods design enabled initial quantitative mapping of student perceptions across 149 participants from four campuses, followed by qualitative exploration of underlying mechanisms through 24 participants in interviews and focus groups. Data generation methods were framed by SDL and TAM frameworks within constructivist epistemology, ensuring theoretical consistency throughout the investigation. Multiple analytical approaches, descriptive statistics, thematic analysis, content analysis, and comparative analysis, were employed to generate comprehensive understanding of the phenomenon.

Detailed accounts were provided of the ethical considerations taken, including ethical clearance protocols, informed consent procedures, power dynamic mitigation strategies, and confidentiality safeguards, along with criteria ensuring a rigorous study through validity, reliability, and trustworthiness frameworks. Methodological limitations were transparently acknowledged, including self-report bias, cross-sectional design constraints, single-campus qualitative sampling, and researcher positionality

considerations. These limitations inform appropriate interpretation of findings while the methodological strengths provide confidence in study conclusions.

The methodological considerations of this mixed-methods study have therefore ensured that sufficient contextual data was generated, triangulating findings through the analysis of quantitative and qualitative data, validating the results and enriching the study's outcomes (Sharma et al., 2023; Draucker, 2020). Chapter 4 commences the presentation of the study's findings, focusing on the quantitative phase of the study.

Chapter 4: Presentation and Interpretation of Findings (Quantitative Phase): Students' Learning Experiences with AI-Generated Resources in ACC1A

4.1 Introduction

This chapter presents and interprets quantitative findings from 149 first-year Accounting (ACC1A) students at Emeritus College following their eight-week engagement with a customised Generative AI tool. The chapter addresses Research Question 1: What are first year students' learning experiences of engaging with AI-generated lecture summaries and pathway questions in the ACC1A module?

The quantitative data was collected through an online questionnaire distributed to 416 students between July and September 2025, yielding a 36% response rate ($n=149$). This response rate is acceptable for online surveys, which typically achieve 34-36% participation (Mursa et al., 2025). The questionnaire's reliability was confirmed through Cronbach's alpha ($\alpha = 0.87$), indicating strong internal consistency for the Likert-scale items measuring student perceptions.

The quantitative phase employed descriptive statistics to characterise student experiences and Spearman's rank correlation coefficients to examine relationships between variables. As the exploratory case study focused on understanding experiences rather than testing causal hypotheses, inferential statistics were not employed. The descriptive approach aligns with the study's interpretivist epistemology, which seeks to understand meaning rather than establish generalisable laws (Creswell & Poth, 2018).

Findings are organised into six sections: (1) demographic characteristics of respondents, (2) learning engagement and overall experience, (3) ease of use and confidence, (4) PU across multiple dimensions, (5) perceived benefits with statistical correlations, and (6) technical challenges encountered. Each section presents frequency distributions and correlation analyses, followed by interpretive discussion connecting findings to Self-Directed Learning (SDL) theory, Technology Acceptance Model (TAM), and literature on AI in education.

Three key patterns emerged from the data. First, while the majority of students (48-58%) perceived AI resources as useful for assessment preparation and conceptual understanding, nearly half of respondents (40-47%) selected neutral responses

across multiple constructs, suggesting conditional or context-dependent experiences. Second, strong positive correlations between EOU and PU ($p = 0.692$, $p < 0.01$) indicate that usability significantly influences learning benefits. Third, students valued AI resources primarily for instrumental goals, exam preparation ranked highest, revealing strategic rather than intrinsic learning orientations.

These findings generate both confirmatory and challenging implications for educational theory. The strong relationship between usability and perceived benefits confirms Technology Acceptance Model predictions (Davis, 1989), while students' instrumental orientation creates tension with Self-Directed Learning theory's emphasis on autonomous, intrinsically motivated learning (Garrison, 1997). The substantial neutral responses suggest that AI tool effectiveness varies considerably across individuals, warranting qualitative exploration of the conditions and contexts that mediate learning benefits.

4.1.1 Theoretical Lens for Interpreting Quantitative Findings

Findings are interpreted through two complementary theoretical frameworks established in Chapter 2. Self-Directed Learning (SDL) theory, the study's primary framework, posits that effective learners exhibit self-management (planning and executing learning activities), self-monitoring (evaluating progress), and intrinsic motivation (internal drive to learn) (Garrison, 1997; Knowles, 1975). In technology-enhanced learning contexts, SDL theory predicts that tools supporting learner autonomy, providing flexible access to resources, and facilitating self-assessment will enhance learning outcomes and be perceived as valuable by students.

Technology Acceptance Model (TAM), developed by Davis (1989), provides complementary insights into how students evaluate and adopt educational technologies. TAM proposes that two beliefs, PU (the degree to which technology improves performance) and PEOU (the degree to which technology is effortless), predict technology acceptance and behavioural intention to use. TAM further suggests these beliefs mediate the relationship between system characteristics and actual usage, meaning even pedagogically sound tools will be underutilised if students find them difficult or unhelpful.

4.2 Demographic Representation of Respondents

The demographic profile of the 149 questionnaire respondents reveals important contextual characteristics shaping the interpretation of subsequent findings.

4.2.1 Distribution by Gender

Figure 5 presents the distribution of respondents by gender.

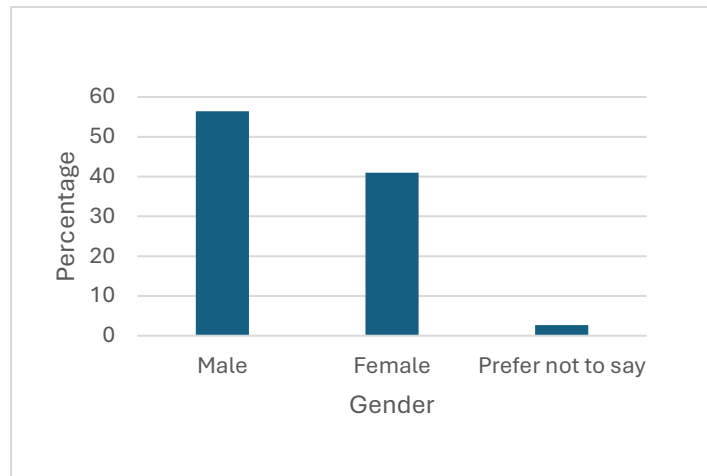


Figure 5: Distribution of respondents by gender

The gender distribution slightly overrepresents male students compared to the ACC1A cohort composition, suggesting potential gender-based response bias. These demographic characteristics warrants noting as it may influence interpretation if gender moderates AI tool perceptions, a possibility not tested due to sample size constraints but acknowledged as a limitation.

4.2.2 Distribution by Age

Figure 6 presents the distribution of respondents by age.

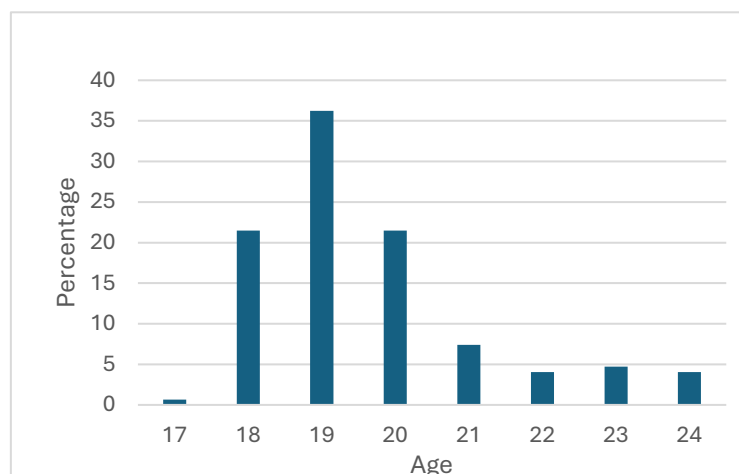


Figure 6: Distribution of respondents by age

The age distribution reflects typical first-year undergraduate profiles in South African higher education, demonstrating a concentration within the 18-24 year age range (Mafunda & Swart, 2020). This distribution suggests findings reflect perspectives of traditional-age undergraduate students rather than mature learners, who may approach technology and self-directed learning differently (Knowles, 1975). The relative age homogeneity strengthens internal validity, reducing age-related confounds, but limits transferability to older student populations.

4.2.3 Distribution by Campus

Figure 7 presents the distribution of respondents by campus.

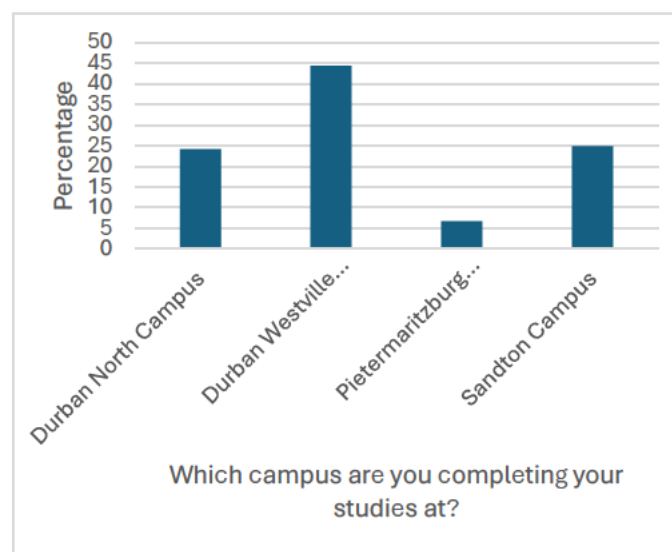


Figure 7: Distribution of respondents by campus

The distribution of respondents across the four campuses did not align with the institutional enrolment pattern at Emeritus College, as the Sandton campus hosted the largest ACC1A cohort, followed by Durban North, then Westville and finally Pietermaritzburg. Campus location potentially introduces contextual variation. Westville serves a socioeconomically diverse population in a suburban area with mixed infrastructure quality, while Sandton operates in an affluent urban business district with robust technological infrastructure. Pietermaritzburg, a smaller regional campus, faces different resource constraints. These geographic and socioeconomic differences may influence students' access to technology, prior digital literacy, and comfort with AI tools. Ideally, cross-campus comparisons would assess whether perceptions varied by location; however, sample sizes within smaller campuses (particularly Pietermaritzburg, $n=10$), as well as the misalignment between the ACC1A

cohort versus the number of respondents per campus, precluded robust statistical testing. This remains a limitation requiring acknowledgement.

4.2.4 Distribution by Prior AI Tool Usage

Figure 8 presents the frequency of respondents based on prior AI tool usage.

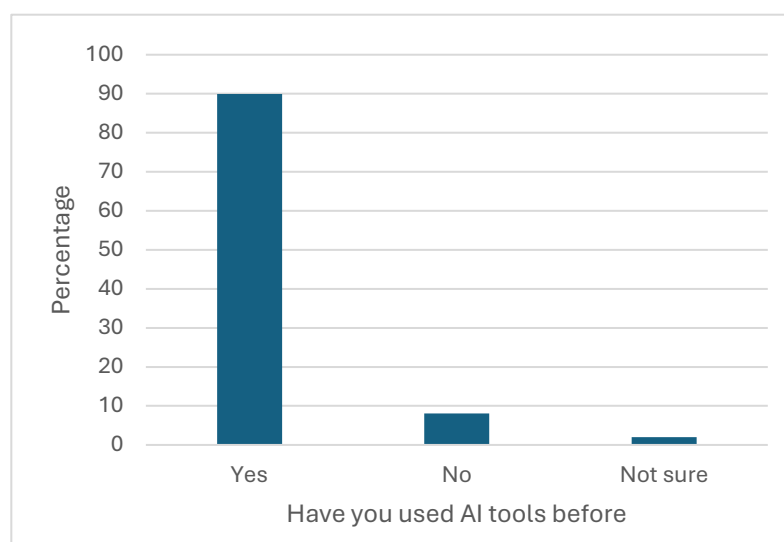


Figure 8: Distribution of responses based on use of AI tools

Majority of the respondents reported prior experience using AI tools before encountering the customised Generative AI resource in ACC1A. This finding substantially contextualises subsequent perceptions. Students evaluated the customised AI tool against existing AI experiences rather than experiencing AI for the first time. From a Technology Acceptance Model perspective, prior experience significantly influences PEOU and usefulness (Venkatesh & Davis, 2000). Students familiar with ChatGPT, Google Bard, or other AI applications possess baseline technological schemas that shape expectations and facilitate adoption. However, this prior experience creates a higher comparison standard, students may judge the customised tool not as "better than nothing" but as "better or worse than alternatives already available." This comparative evaluation framework may explain the substantial neutral responses observed across constructs (discussed in subsequent sections): students may have perceived the customised tool as comparable to, but not substantially superior to, generic AI resources already in their learning toolkit.

The small proportion of AI novices prevented statistical comparison between experienced and inexperienced users, an unfortunate limitation. Ideally, the study would test whether prior AI experience moderated perceptions of usefulness, ease of use, or learning benefits. Such analysis would illuminate whether customised educational AI tools provide differential value depending on students' technological familiarity. This remains an important question for future research as AI becomes increasingly ubiquitous in students' academic and personal lives.

4.2.5 Implications of Demographic Profile

Synthesising demographic characteristics reveals a respondent profile of predominantly young (18-24 years), technologically experienced (90% prior AI use), relatively balanced by gender (56% male, 41% female), distributed across multiple campuses reflecting varied socioeconomic contexts. This profile shapes interpretation in three ways.

First, the high prior AI experience means findings reflect perceptions of technologically literate students rather than novices encountering AI for the first time. The study examines whether customised, pedagogically designed AI tools provide value beyond generic alternatives, not whether AI itself supports learning.

Second, the traditional undergraduate age range suggests findings may not transfer to mature learners or postgraduate students, who demonstrate different learning orientations and technological comfort levels (Knowles, 1975).

Third, the campus diversity introduces potential contextual variation not systematically analysed due to sample constraints. Findings represent aggregated perspectives across different institutional micro-contexts, a strength for ecological validity but a limitation for understanding localised factors influencing AI tool effectiveness.

These demographic considerations inform subsequent interpretation, particularly when patterns diverge from prior research conducted in different contexts with different student populations.

4.3 Learning Engagement and Overall Learning Experience

This section examines students' perceptions of how AI-generated resources influenced their engagement with learning content and their overall learning experience in ACC1A.

4.3.1 Perceived Impact on Learning Engagement

Figure 9 presents the frequency distribution of students' perceptions of the AI tool's impact on their learning engagement.

The AI-generated lecture summaries and homework questions made learning more engaging for me					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly disagree	2	1.3	1.3	1.3
	Disagree	12	8.1	8.1	9.4
	Neutral	68	45.6	45.6	55
	Agree	50	33.6	33.6	88.6
	Strongly agree	17	11.4	11.4	100
	Total	149	100	100	

Figure 9: Frequency of responses - Students' experiences of AI-Generated resources to enhance learning engagement

Combining agreement categories, 45% perceived enhanced engagement, while 9.4% experienced no engagement benefit and 45.6% expressed neutrality. The tripartite distribution, with agreement, neutrality, and disagreement each representing substantial proportions, reveals divided student experiences rather than consensus. The near-equivalence between agreement and neutrality indicates that for every student experiencing enhanced engagement, another felt ambivalent about engagement effects.

Theoretical Interpretation: Self-Directed Learning and Engagement

From a Self-Directed Learning perspective, this finding presents both encouraging and concerning patterns. SDL theory emphasises that intrinsic motivation and active engagement are foundational to autonomous learning (Garrison, 1997). Technologies supporting SDL should enhance engagement by providing learner control, immediate feedback, and personalised pacing, all characteristics theoretically embedded in the customised AI tool design. The 45% who reported enhanced engagement align with SDL predictions, suggesting the tool successfully facilitated active learning for a substantial minority.

However, the 45.6% neutral response challenges SDL assumptions. Garrison's (1997) model presumes that resources supporting autonomy naturally enhance motivation and engagement. The ambivalence suggests that either, (1) the AI tool did not

effectively support SDL dimensions for many students, (2) students varied in their readiness for self-directed learning, with only SDL-ready individuals benefiting, or (3) engagement benefits were conditional, present in some learning contexts but not others, producing mixed overall impressions.

The small proportion disagreeing (9.4%) merits attention despite its minority status. These students actively perceived the AI resources as failing to enhance engagement. Literature on technology acceptance suggests that when users experience disconfirmed expectations, anticipating benefits that fail to materialise, they respond more negatively than users with no prior expectations (Venkatesh & Davis, 2000). Students in this category may have expected AI to substantially transform their learning experience but found it comparable to or worse than traditional resources, producing disappointment manifesting as disagreement.

Comparison to Literature

These findings contrast with predominantly positive student perceptions reported in recent AI-in-education literature. Stohr et al. (2024) found 56% of students reported positive perceptions towards the use of AI learning tools. Vieriu & Petrea (2025) and Sustaningram & Haldaka (2025) confirm an 80% agreeance with statements that suggest that the use of AI enhances educational experience and provides substantial academic benefit. Our lower agreement rate (45%) and higher neutrality (45.6%) suggest engagement benefits may be more conditional than previous research implies. This aligns with the study of Sousa & Cardoso (2025) which established a 53.5% agreement on enhanced learning engagement and 38.8% neutrality, prefacing differences due to individual student preferences. Similarly, Arowosegbe et al. (2024) documented a split between agreeance and neutrality, revealing a 40% agreeance percentage (ie. positive perception) versus 39% neutrality pertaining to the overall perception of Generative AI in UK higher education. Neutrality within this study could be understood as the difference between students' perceptions based on age, with 18 to 24 year old students holding a more negative perception versus those aged between 25 and 34, indicating a difference between undergraduate versus postgraduate views. This substantiates the argument that engagement is conditional.

Several factors may explain the discrepancy within this case study. First, prior studies often examined students' general impressions of AI tools; this study measured specific

experiences with a particular customised tool, potentially yielding more nuanced, critical responses. Second, comparative studies typically survey students after brief exposure (1-3 weeks); this study collected data after eight weeks of use, potentially capturing honeymoon effect decay as initial enthusiasm waned. Third, the high proportion of students with prior AI experience (89.9%) creates a higher comparison standard, students may have benchmarked the tool against alternatives rather than comparing "AI versus no AI."

Implications for Practice

The substantial neutral responses (45.6%) hold important practical implications. These students neither endorsed nor rejected engagement benefits, suggesting uncertainty or conditional experiences. From an educational design perspective, neutrality may indicate that engagement benefits depended on factors not controlled in implementation, perhaps individual learning preferences, specific features used, or alignment between AI content and personal study approaches, as was found to be the case in the studies of Sousa & Cardoso (2025) and Arowosegbe et al. (2024).

This heterogeneity suggests that universal AI tool provision is insufficient; differentiated support may be necessary. Students who experienced engagement benefits likely needed minimal intervention, while ambivalent students may have required scaffolding to leverage AI effectively, explicit instruction on when and how to use summaries and pathway questions, modelling of effective integration into study routines, or metacognitive prompts to reflect on AI's role in their learning process. The 9.4% who disagreed may have needed entirely different approaches, alternative resources, personalised support, or acknowledgement that AI tools do not suit all learning preferences.

4.3.2 Perceived Impact on Overall Learning Experience

Figure 10 presents the frequency distribution of students' perceptions of the AI tool's impact on their overall learning experience.

The use of AI-generated resources in the ACC1A module improved my overall learning experience					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly disagree	2	1.3	1.3	1.3

Disagree	16	10.7	10.7	12.1
Neutral	66	44.3	44.3	56.4
Agree	51	34.2	34.2	90.6
Strongly agree	14	9.4	9.4	100
Total	149	100	100	

Figure 10: Frequency of responses - Students' experiences of AI-Generated resources to improve their overall learning experience

Combined agreement reached 43.6%, disagreement 12%, and neutrality 44.3%. The persistence of high neutrality across both engagement and overall experience constructs suggests this ambivalence represents a genuine response pattern rather than survey fatigue or confusion. Students who felt neutral about engagement also felt neutral about overall learning experience, indicating consistent conditional or mixed impressions across related constructs.

Interpreting Neutrality: Beyond Ambivalence

The substantial neutral responses require deeper consideration than simply labelling students as "ambivalent." Research on Likert-scale interpretation suggests respondents select "neutral" for multiple reasons (Kulas & Stachowski, 2009):

1. True ambivalence: Experiencing both positive and negative aspects, producing genuine mixed feelings
2. Conditional experiences: Benefits present in some contexts but not others (e.g., useful for some topics but not all)
3. Modest effects: Perceiving slight improvements insufficient to warrant "agree" but not negative enough to select "disagree"
4. Comparison to alternatives: Perceiving AI as comparable to existing resources, neither better nor worse
5. Uncertainty: Lacking clear sense of whether learning improved or not

Without qualitative data clarifying what "neutral" meant to students, interpretation remains speculative. However, the 89.9% prior AI experience suggests the fourth explanation, comparison to alternatives, may be particularly salient. Students accustomed to using ChatGPT or other AI tools may have found the customised tool

functionally equivalent, producing neutrality reflecting "no better than what I already use" rather than genuine ambivalence.

Self-Directed Learning Perspective

SDL theory would predict that tools supporting learner autonomy improve overall learning experiences by enabling students to control pacing, focus on personally relevant content, and receive immediate feedback (Garrison, 1997). The 43.6% who agreed that AI improved their learning experience align with these predictions. These students likely utilised the tool's self-directed features, accessing summaries on-demand, attempting pathway questions at self-selected times, and revisiting content as needed.

However, SDL theory also recognises that student readiness varies, as acknowledged by Guglielmino's Self Directed Learning Readiness scale developed in 1977 (Piratheeban & Bandara, 2025). Students with higher SDL readiness, possessing intrinsic motivation, self-management skills, and self-monitoring capabilities, are better positioned to leverage autonomous learning tools effectively. Students lacking these competencies may require greater structure and guidance, meaning technology enabling autonomy could overwhelm rather than empower them. The 44.3% neutral and 12% disagreement may partially reflect students at earlier stages of SDL development, for whom flexible, autonomous access to resources proved less beneficial than structured, instructor-guided learning.

Practical Implications

The finding that fewer than half of students agreed AI improved their overall learning experience challenges the assumption that providing educational technology automatically enhances learning. This pattern aligns with Cuban's (2001) critique of technological determinism, the belief that tools themselves drive improvement regardless of pedagogical integration, learner characteristics, or contextual factors.

For institutional implementation, findings suggest AI tool provision should accompany:

- Explicit orientation: Students may not intuitively understand optimal AI tool usage, requiring instruction on effective integration into study routines

- Differentiated support: High SDL-readiness students may thrive with minimal guidance, while others need scaffolded introduction and ongoing support
- Ongoing evaluation: Rather than assuming universal benefit, institutions should regularly assess which students benefit and why, adjusting implementation accordingly

4.3.3 Qualitative Exploration of Neutral Responses

Recognising the substantial neutral responses as a key finding, the qualitative phase (Chapter 5) specifically probed reasons for ambivalence through focus group questions which served to assess students' conditional experiences. This was achieved by engaging students in a reflective activity pertaining to when they found the AI-generated resources as being helpful versus a time when it was unhelpful or overwhelming. Preliminary qualitative findings (discussed extensively in Chapter 5) suggest neutrality reflected three primary patterns:

1. Feature-specific variation: Students found lecture summaries and pathway questions were useful to understand Accounting theory but the pathway questions less useful due to a technical challenge related to marking of quiz responses and its superficial nature to engage students with Accounting concepts, producing mixed overall impressions
2. Topic-dependent effectiveness: AI summaries clarified basic Accounting concepts (e.g., debtors and creditors) but struggled with complex application (e.g., VAT and General Ledger), creating variable experiences
3. Comparison to alternatives: Students perceived the customised tool as being inadequate when compared to other AI tools such as Quizlet and Turbolearn, already in their toolkit, producing neutrality based on equivalence in some areas but inferiority in others.

These qualitative insights (fully developed in Chapter 5 and integrated in Chapter 6) help explain the quantitative neutrality pattern, demonstrating the value of mixed-methods design in capturing nuanced experiences inadequately represented by numerical data alone.

4.4 Ease of Use and Confidence Using the AI Tool

This section examines two interrelated perceptions, whether students found AI resources easy to understand and use, and whether they felt confident employing the tool to support their learning.

4.4.1 Perceived Ease of Use

Figure 11 represents the frequency distribution of students' perceptions of the ease of use of the AI-generated lecture summaries.

The AI-generated lecture summaries were easy to understand and follow					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly disagree	3	2	2	2
	Disagree	4	2.7	2.7	4.7
	Neutral	60	40.3	40.3	45
	Agree	66	44.3	44.3	89.3
	Strongly agree	16	10.7	10.7	100
	Total	149	100	100	

Figure 11: Frequencies related to the ease of use of the AI-generated lecture summaries

Agreement was 55%, with 4.7% disagreement and 40.3% neutrality, indicating that ease of use was the most positively evaluated construct. This pattern suggests the AI tool's interface and content design achieved baseline usability for most students; lecture summaries were comprehensible, well-structured, and accessible.

Technology Acceptance Model Perspective

TAM identifies PEOU as a foundational determinant of technology acceptance (Davis, 1989). When users perceive technology as requiring excessive effort, confusing interfaces, unclear navigation, or cognitively demanding interaction, adoption declines even if the tool offers potential benefits. Conversely, easy-to-use technologies reduce barriers to adoption, increasing likelihood of sustained engagement.

The 55% majority agreement on ease of use indicates the customised AI tool met usability standards for most students. This is methodologically important. If students had found the tool difficult to use, negative perceptions of usefulness or learning benefits might reflect usability failures rather than genuine pedagogical shortcomings.

The relatively high ease-of-use ratings suggest subsequent findings about usefulness more validly reflect educational value rather than interface problems.

However, the persistent 40.3% neutrality warrants examination. Even on the most positively rated construct, substantial ambivalence remains. Potential explanations include:

Content Complexity Variation: Accounting concepts range from straightforward (basic definitions, simple calculations) to complex (integrated financial statements, conceptual framework application). AI-generated summaries may have varied in clarity depending on underlying concept complexity. Students may have found some summaries exceptionally clear while struggling with others, producing overall ambivalence.

Comparison Standards: Students with extensive prior AI experience (89.9%) possess comparison points. Those accustomed to other AI tools might have found the structured summaries comparably easy, producing neutrality reflecting equivalence rather than difficulty.

Individual Differences in Digital Literacy: While most students had prior AI experience, comfort with technology varies. Students who were confident in a digital environment, using their cellphone as the interface, may have found the AI-generated resources very easy to access and navigate, while those less comfortable experienced greater cognitive loads, with aggregated responses producing moderate means manifesting as neutrality.

Practical Implications

The relatively high ease-of-use ratings (55% agreement) validate the tool's usability design but also reveal opportunities for improvement. The 40.3% neutral responses suggest room for enhanced clarity, potentially through:

- Varied presentation formats: Some students may prefer visual representations (diagrams, flowcharts) while others prefer textual summaries
- Progressive disclosure: Complex topics might benefit from layered information, basic overviews accessible initially, with detailed explanations available on-demand

- Worked examples: Abstract concepts may become clearer through concrete examples integrated into summaries

The minimal disagreement (4.7%) is encouraging, suggesting few students found summaries genuinely difficult. However, even small numbers matter, seven students experienced usability challenges potentially excluding them from learning benefits others accessed easily.

4.4.2 Confidence to Use the AI Tool

Figure 12 represents the frequency distribution of students' responses related to their confidence to use the AI tool.

I felt confident in using the MathU platform to assist with my learning in the ACC1A module					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly disagree	6	4	4	4
	Disagree	12	8.1	8.1	12.1
	Neutral	71	47.7	47.7	59.7
	Agree	45	30.2	30.2	89.9
	Strongly agree	15	10.1	10.1	100
	Total	149	100	100	

Figure 12: Frequencies related to students' confidence to use the customised Generative AI tool

Combined agreement reached 40.3%, disagreement 12.1%, and neutrality 47.7%. Confidence levels decreased relative to EOU. While 55% found the tool easy to use, only 40.3% felt confident using it. This discrepancy suggests that perceived ease and confidence, though related, represent distinct psychological constructs. Students may recognise a tool as objectively easy to navigate yet lack subjective confidence in their ability to use it effectively, a finding consistent with self-efficacy literature emanating from Bandura's self-efficacy theory distinguishing between task difficulty perception and personal capability beliefs.

Self-Efficacy Theory Perspective

Bandura's self-efficacy theory, coined in 1997, distinguishes between outcome expectations (believing a tool can produce results) and efficacy expectations (believing oneself capable of using the tool effectively) (Yavich et al., 2025). Students may have perceived AI summaries as potentially useful (outcome expectations) while doubting

their ability to leverage them appropriately (efficacy expectations). This distinction helps explain the gap between the 55% who found the tool easy to use and the 40.3% who felt confident using it.

In educational technology contexts, Compeau and Higgins (1995) demonstrated that computer self-efficacy, confidence in one's technological capabilities, predicts learning outcomes beyond actual skill levels. Students with low technology self-efficacy underutilise available resources despite possessing requisite skills, while high-self-efficacy students maximise tool benefits. Applied here, the 47.7% neutral and 12.1% disagreement on confidence may represent students who recognised the tool's usability but doubted their capacity to integrate it effectively into learning routines.

From a Self-Directed Learning perspective, this finding is particularly concerning. SDL requires learners to make strategic decisions about resource selection and usage (Garrison, 1997). Low-confidence students may avoid using AI resources despite availability, missing potential benefits, or may use them ineffectively, consulting summaries passively rather than actively engaging with content. Building confidence alongside providing tools is essential for SDL-supportive interventions.

4.4.3 Relationship Between Ease of Use and Confidence

To examine whether ease of use predicted confidence, Spearman's rank correlation coefficient was computed. Figure 13 presents the relationship as statistically significant and positive ($\rho = 0.358$, $p < 0.01$), indicating students who found AI summaries easy to understand were more likely to feel confident using the tool. This correlation, while significant, is moderate in strength (Cohen, 1988), EOU explained approximately 13% of variance in confidence ($r^2 \approx .13$), meaning other factors substantially contributed to confidence levels.

Correlation Interpretation		I felt confident in using the AI tool to assist with my learning in the ACC1A module
$ \rho < 0.3$	Small	
$0.3 < \rho < 0.59$	Medium	
$ \rho > 0.6$	Large	
The AI-generated lecture summaries were easy to understand and follow		,358** ($\rho = 0.358$, $p < 0.01$)

Figure 13: Correlation between ease of use and confidence to use the customised Generative AI Tool

To validate this finding, a chi-square test of independence examined whether EOU responses associated with confidence responses. The association was statistically significant with a large effect size ($\chi^2(16) = 98.849, p < 0.001$, Cramer's $V = 0.407$). Using Cramer's V guidelines (Cohen, 1988), as presented in Figure 14, a value of 0.407 represents a large effect in a contingency table of this size, confirming a strong relationship between ease of use and confidence.

DF	Small Effect	Medium Effect	Large Effect
4+	0.05	0.15	0.25

Figure 14: Guideline used to assess the strength between the association between statements

Interpreting the Correlation

The significant positive correlation between EOU and confidence aligns with self-efficacy theory's mastery experiences principle, positing that successful performance (finding something easy) builds confidence in one's capabilities (Bandura, 1997). When students encountered clear, comprehensible AI summaries, they developed confidence in their ability to use the tool effectively. Conversely, students who struggled with summaries developed doubts about their technological competence, reducing confidence.

However, the moderate correlation strength ($\rho = 0.358$) indicates ease of use does not fully determine confidence. Students who found the tool easy did not automatically feel confident, and some students who experienced usability challenges nonetheless persevered confidently. This suggests individual difference factors, prior technological self-efficacy, general confidence in learning, personality traits like persistence or self-assurance, mediate the ease-confidence relationship.

Technology Acceptance Model Implications

TAM posits that PEOU influences PU and intention to use technology (Li, 2023). The ease-confidence correlation extends TAM by demonstrating that usability affects not only perceptions of tool value but also users' psychological readiness to engage with tools. This has design implications. Even pedagogically sound AI resources will be underutilised if students lack confidence to employ them. Confidence-building

measures, tutorials, peer modelling, low-stakes practice opportunities, may be as important as technical usability in promoting adoption.

Practical Implications for Implementation

The finding that ease of use influences but does not determine confidence suggests institutions should invest in both technical usability and psychological support:

Usability Design: Continuing to refine interface clarity, navigation simplicity, and content comprehensibility remains essential. The 4.7% who found summaries difficult and 40.3% who felt neutral about ease represent opportunities for improvement.

Confidence-Building Interventions: Beyond usability, institutions should provide:

- **Demonstration sessions:** Showing students how to integrate AI into study routines
- **Peer testimonials:** Allowing confident users to share strategies with uncertain peers
- **Low-stakes practice:** Encouraging experimentation without assessment consequences
- **Metacognitive prompts:** Asking students to reflect on how AI supports their learning, building awareness of its value

Differentiated Support: Students entering with low technological self-efficacy require targeted interventions. Identifying these students early (perhaps through self-efficacy surveys) enables proactive support before underutilisation becomes habitual.

The moderate correlation also suggests that even with optimal usability, some students will lack confidence due to factors beyond tool design, general academic self-doubt, technology anxiety, or limited prior experience. Holistic support addressing these broader confidence issues may be necessary alongside AI tool provision.

4.5 Perceived Usefulness Across Multiple Dimensions

This section examines students' perceptions of AI resources' usefulness for various learning purposes including reinforcing learning, preparing for assessments, supplementing traditional materials, and understanding key concepts. Figure 15 groups these related constructs, enabling an examination of usefulness as a multidimensional construct rather than a monolithic perception.

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree	Agree & Strongly Agree
	Row N %	Row N %	Row N %	Row N %	Row N %	Row N %
The AI-generated homework questions helped me reinforce my learning and improved my understanding of the material	4.00%	7.40%	43.00%	36.20%	9.40%	46%
The AI-generated homework questions were useful in preparing me for exams and assessments	2.70%	4.70%	34.90%	47.70%	10.10%	58%
AI-generated resources are a useful supplement to traditional learning materials (like the textbook and module guide) in the ACC1A module	2.70%	9.40%	38.30%	33.60%	16.10%	50%
The AI-generated lecture summaries helped me understand the key concepts of the ACC1A module	3.40%	2.70%	45.60%	39.60%	8.70%	48%

Figure 15: Frequencies of statements related to the construct of PU

4.5.1 Usefulness for Learning Reinforcement

Combined agreement reached 45.6%, disagreement 11.4%, and neutrality 43%.

4.5.2 Usefulness for Assessment Preparation

Combined agreement reached 57.8%, the highest across all constructs, with disagreement at 7.4% and neutrality 34.9%.

4.5.3 Usefulness as Supplementary Resource

Combined agreement reached 49.7%, disagreement 12.1%, and neutrality 38.3%.

4.5.4 Usefulness for Understanding Key Concepts

Combined agreement reached 48.3%, disagreement 6.1%, and neutrality 45.6%.

4.5.5 Comparative Analysis of Usefulness Dimensions

Figure 16 ranks constructs by combined agreement revealing a clear hierarchy:

Rank 1: Assessment preparation (57.8%) – Highest agreement

Rank 2: Ease of use (55%) – Previously discussed

Rank 3: Supplementary resource (49.7%)

Rank 4: Understanding key concepts (48.3%)

Rank 5: Learning reinforcement (45.6%)

Ranking	Statement	Strongly disagree	Disagree	Neutral	Agree	Strongly Agree	Agree & Strongly Agree
		Row N %	Row N %	Row N %	Row N %	Row N %	Row N %
1	The AI-generated homework questions were useful in preparing me for exams and assessments	2.70%	4.70%	34.90%	47.70%	10.10%	58%
2	The AI-generated lecture summaries were easy to understand and follow	2.00%	2.70%	40.30%	44.30%	10.70%	55%
3	AI-generated resources are a useful supplement to traditional learning materials (like the textbook and module guide) in the ACC1A module	2.70%	9.40%	38.30%	33.60%	16.10%	50%
4	The AI-generated lecture summaries helped me understand the key concepts of the ACC1A module	3.40%	2.70%	45.60%	39.60%	8.70%	48%
5	The AI-generated homework questions helped me reinforce my learning and improved my understanding of the material	4.00%	7.40%	43.00%	36.20%	9.40%	46%

Figure 16: Frequencies of statements where the level of agreeance is higher than the percentage of neutral responses (top 5 ranking based on percentage total agreeance)

This ranking pattern reveals students' value orientations toward AI resources. Most significantly, instrumental benefits (assessment preparation, exam success) ranked highest, while intrinsic learning benefits (understanding concepts, reinforcing learning) ranked lower. Students valued AI primarily for achieving performance goals rather than deepening conceptual mastery or satisfying intellectual curiosity.

Theoretical Implications: SDL Theory Under Tension

This instrumental orientation creates substantial tension with Self-Directed Learning theory. SDL emphasises intrinsic motivation, learning driven by personal interest, curiosity, and desire for competence rather than external rewards like grades (Garrison, 1997; Knowles, 1975). Knowles argued that mature, self-directed learners pursue knowledge for its inherent value, developing internal learning agendas independent of assessment requirements. However, first-year Accounting students demonstrated clearly instrumental orientations. The highest-ranked benefit, exam preparation usefulness (57.8%), reflects strategic, assessment-focused learning. Students approached AI as a tool for achieving grades rather than exploring Accounting concepts intrinsically. This pattern aligns with Biggs' (1987) distinction between surface and deep learning approaches whereby surface learners focus on memorisation and reproduction for assessment, while deep learners seek understanding and meaning-making. The prominence of exam preparation suggests many students adopted surface approaches to AI resource usage.

This finding should not be interpreted as a deficit in students but rather as a realistic appraisal of higher education contexts, particularly in South Africa where high-stakes assessment determines progression and high attrition rates create intense performance pressure (Maree, 2015). Students rationally prioritise resources supporting survival and success in assessment-driven systems. The question becomes not whether students should be more intrinsically motivated, but whether and how AI tools can serve instrumental goals while simultaneously promoting deeper learning.

Constructive Interpretation: Instrumental-Intrinsic Coexistence

While exam preparation ranked highest, understanding key concepts ranked fourth (48.3%), still representing a substantial minority. Moreover, Spearman's correlation between these constructs (discussed in section 4.6.1) revealed strong positive association ($\rho = 0.563$, $p < 0.01$), indicating students who valued AI for exam preparation also valued it for conceptual understanding. This suggests instrumental and intrinsic motivations coexisted rather than representing opposing orientations.

Students may recognise, accurately, that Accounting exam success requires genuine understanding, not merely memorisation. ACC1A assessments include application

and analysis questions demanding conceptual grasp, making understanding instrumentally valuable. Thus, students simultaneously pursued both goals, understanding concepts because doing so supports exam performance. This synthesis of instrumental and intrinsic goals represents pragmatic learning orientation appropriate for high-stakes academic contexts.

Comparison to Literature

The instrumental orientation aligns with recent research on student technology use. Bosch et al. (2023) found South African students valued AI tools primarily for assessment support, while Muringa (2025) documented that students leveraged AI strategically for learning and understanding, idea generation and structuring for assignments. Our findings confirm these patterns while extending understanding by quantifying the relative priority of instrumental over intrinsic benefits.

However, our instrumental focus contrasts with Western studies emphasising intrinsic learning benefits. The largest survey on students' use of AI, specifically ChatGPT, established that students view the greatest benefit as being an engaging learning tool (Ravselj et al., 2025). These higher intrinsic motivation rates may reflect different educational cultures, Western universities emphasising liberal education and intellectual exploration versus South African contexts prioritising credentialing and employment preparation (Swartz et al., 2019). Alternatively, differences may reflect methodological variation, generic questions about "AI tools" versus specific questions about particular tools in specific courses.

Implications for AI Tool Design

The prominence of instrumental benefits suggests pedagogical design strategies for leveraging students' pragmatic orientations while promoting deeper learning:

Strategic Alignment: Rather than resisting students' assessment focus, design AI tools that explicitly support exam success through deep learning. For example, pathway questions requiring application and analysis (not recall) teach higher-order thinking while addressing assessment preparation needs.

Transparent Value Propositions: Communicate clearly how AI resources support exam performance, legitimising students' instrumental goals while demonstrating that conceptual understanding is the pathway to assessment success.

Formative Assessment Integration: Embed AI-generated questions within low-stakes quizzes or self-assessments, creating opportunities to practice exam-type questions while receiving immediate feedback that scaffolds understanding.

Metacognitive Prompts: After completing AI-generated questions, prompt reflection: "What concept did this question test?" "What misconceptions did you discover?" Such prompts shift focus from "getting answers right" to "understanding why answers are right," gradually cultivating deeper learning habits.

The findings do not suggest students are incapable of intrinsic motivation; rather, they reveal realistic prioritisation given contextual pressures. Effective AI integration acknowledges these priorities while designing experiences that make deep learning instrumentally valuable.

4.5.6 Patterns in Neutral Responses

Neutrality rates varied across usefulness dimensions:

- Assessment preparation: 34.9% (lowest neutrality)
- Ease of use: 40.3%
- Supplementary resource: 38.3%
- Understanding concepts: 45.6%
- Learning reinforcement: 43%

The inverse relationship between agreement and neutrality is notable revealing assessment preparation, with the highest agreement (57.8%), exhibited the lowest neutrality (34.9%). Conversely, learning reinforcement, with lower agreement (45.6%), showed higher neutrality (43%). This pattern suggests students held clearer opinions, positive or negative, about instrumental benefits but felt more uncertain about intrinsic learning benefits.

Psychologically, this makes sense. Students can readily assess whether AI questions resembled exam formats or helped practice assessment skills, concrete, observable outcomes. However, evaluating whether AI "reinforced learning" or "enhanced understanding" requires metacognitive judgments about internal cognitive states,

which students may find more difficult to assess, producing greater uncertainty manifesting as neutrality.

This interpretation suggests neutral responses on intrinsic benefit items may reflect measurement challenges rather than genuine ambivalence. Students may have genuinely benefited from conceptual reinforcement but lacked confidence in judging whether learning improved, producing neutral responses despite actual benefits. Alternatively, intrinsic benefits may accrue gradually over time, making them less salient in retrospective surveys than immediate instrumental outcomes like exam preparation.

4.6 Perceived Benefits: Statistical Relationships and Value Propositions

Building on the descriptive findings about PU, this section examines statistical relationships between constructs to identify which factors predict perceived benefits and to conceptualise the value dimensions students associated with AI resources.

4.6.1 Factors Predicting Perceived Usefulness as Supplementary Resource

Multiple statements correlated significantly with students' perception that AI resources were useful supplements to traditional materials. Figure 17 presents these relationships.

Predictor Statement	Spearman's ρ	p-value	Interpretation
The AI-generated lecture summaries helped me understand the key concepts of the ACC1A module	0.518**	<0.01	Large positive correlation
The AI-generated homework questions helped me reinforce my learning and improved my understanding of the material	0.442**	<0.01	Moderate positive correlation
The AI-generated homework questions were useful in preparing me for exams and assessments	0.401**	<0.01	Moderate positive correlation
The AI-generated lecture summaries and homework	0.453**	<0.01	Moderate positive correlation

questions made learning more engaging for me			
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Figure 17: Correlations with PU as Supplementary Resource

All relationships proved statistically significant and positive, indicating students who perceived specific benefits (conceptual understanding, learning reinforcement, assessment preparation, engagement) were substantially more likely to view AI resources as useful supplements overall. Using Cohen's (1988) guidelines for correlation magnitude (small: $\rho = .10-.29$; medium: $\rho = .30-.49$; large: $\rho \geq .50$), the relationship between understanding concepts and supplementary usefulness qualifies as large ($\rho = 0.518$), while others represent moderate associations.

The strongest relationship, between conceptual understanding and supplementary value ($\rho = 0.518$), suggests students judged supplementary usefulness primarily through the lens of whether AI resources enhanced comprehension. This finding aligns with constructivist learning theory which characterises effective learning resources as those facilitating meaning-making and conceptual integration (Jonassen, 2000; Vygotsky, 1978). AI summaries and questions functioned as cognitive tools, mediating artifacts scaffolding understanding, and students who experienced this scaffolding effect perceived AI as a valuable supplement.

The moderate correlation with assessment preparation ($\rho = 0.401$) suggests instrumental value also contributed to supplementary usefulness perceptions, though less strongly than conceptual understanding. This finding complicates the instrumental-intrinsic distinction discussed earlier, whereby students valued AI resources as supplements primarily because they enhanced understanding, not merely because they supported exam preparation. This more nuanced interpretation suggests students recognised that effective supplementary resources should deepen learning rather than simply providing additional assessment practice.

4.6.2 Relationships Between Supplementary Value, Learning Experience, and Behavioural Intentions

Figure 18 presents two additional correlations which illuminates the consequences of perceiving AI as a useful supplementary resource:

Predictor Statement	Spearman's ρ	p-value	Interpretation
The use of AI-generated resources in the ACC1A module improved my overall learning experience	0.503**	<0.01	Large positive correlation
I would prefer to have more AI-generated resources integrated into learning materials for the ACC1A module	0.575**	<0.01	Large positive correlation

Figure 18: Relationship between PU, overall learning experience and preference for more AI-Generated resources

Perceived supplementary value → Overall learning experience: $\rho = 0.503$, $p < 0.01$

Students who viewed AI as useful supplement reported better overall learning experiences in ACC1A, indicating supplementary value directly influenced holistic course satisfaction.

Perceived supplementary value → Preference for more AI resources: $\rho = 0.575$, $p < 0.01$

Students who valued AI as a supplement expressed stronger preference for additional AI integration in the module, demonstrating that perceived value predicts behavioural intentions to continue using technology.

These relationships align with Technology Acceptance Model's core predictions (Davis, 1989): PU predicts both attitudes toward technology (overall learning experience) and behavioural intention to use (preference for more AI resources). The moderate-to-large correlation magnitudes confirm TAM applies in educational AI contexts, when students perceive technology as useful, they develop positive attitudes and intentions to continue adoption.

From a practical perspective, these findings demonstrate the importance of ensuring students experience clear, tangible benefits from AI resources. Without perceived value, students will not advocate for continued use or enthusiastically engage when AI is provided. Conversely, demonstrating value creates positive feedback loops: PU → positive experience → intention to use more → increased engagement → greater benefits realised.

4.6.3 Conceptualising Value Dimensions: A Framework for AI Learning Benefits

The correlation analyses reveal multiple dimensions along which students perceived AI value. Drawing on Wegerif's (2007) framework distinguishing cognitive, instrumental, affective, and social educational value, this study proposes five value dimensions characterising students' AI resource perceptions:

4.6.3.1. Cognitive Value ($p = 0.692$, largest correlation)

The strongest relationship identified was between EOU and conceptual understanding ($p = 0.692$, $p < 0.01$). Students who found AI summaries easy to understand were substantially more likely to report enhanced comprehension of ACC1A concepts. This relationship, validated through chi-square analysis ($\chi^2 (16) = 205.140$, $p < 0.001$, Cramer's $V = 0.587$, large effect size), demonstrates cognitive value as AI resources' primary benefit dimension.

Cognitive value aligns with constructivist learning theory's emphasis on meaning-making (Vygotsky, 1978). AI-generated summaries functioned as cognitive tools by:

- Reducing cognitive load: Summarising dense textbook content into essential concepts, freeing working memory for comprehension rather than information search (Sweller, 1988).
- Providing alternative explanations: Rephrasing textbook language in different terms, offering multiple entry points to understanding
- Highlighting relationships: Explicitly connecting related concepts, supporting schema development

The finding that usability predicted cognitive value underscores the importance of interface design. Complex, confusing AI outputs create cognitive load that overwhelms rather than supports learning. Clear, well-structured summaries enable students to focus cognitive resources on content comprehension rather than navigation or interpretation.

4.6.3.2. Instrumental Value ($p = 0.635$)

The relationship between assessment preparation usefulness and enhanced engagement ($p = 0.635$, $p < 0.01$, validated through $\chi^2 (16) = 200.941$, $p < 0.001$, Cramer's $V = 0.581$) reveals instrumental value as the second major benefit

dimension. Students who found AI resources useful for exam preparation experienced heightened motivation and engagement in learning.

This finding supports expectancy-value theory (Eccles & Wigfield, 2002): students engage more intensely with learning activities when they perceive clear instrumental value, paths to desired outcomes like good grades and course completion. AI resources possessing transparent assessment relevance motivated engagement by making study time feel productive and goal-directed.

However, instrumental value need not contradict deeper learning. As discussed previously, ACC1A assessments require conceptual understanding and application, meaning exam preparation inherently involves substantial cognitive engagement. Students seeking assessment success must master concepts, analyse scenarios, and apply principles, all representing genuine learning. Instrumental value motivated engagement that subsequently produced cognitive benefits, demonstrating how pragmatic student orientations can be pedagogically leveraged.

4.6.3.3. Affective Value ($p = 0.575$)

Two correlations both measuring $p = 0.575$ ($p < 0.01$) reveal affective value:

- Understanding concepts $\rightarrow$ Preference for more AI ($\chi^2 (16) = 100.861$, $p < 0.001$, Cramer's $V = 0.411$)
- Supplementary value $\rightarrow$ Preference for more AI ($\chi^2 (16) = 164.167$, $p < 0.001$, Cramer's $V = 0.525$)

Affective value captures emotional and motivational dimensions. Students who experienced cognitive or instrumental benefits developed positive affect toward AI resources, manifesting as desire for more AI integration. This aligns with self-determination theory (Deci & Ryan, 2000) positing that technologies supporting competence (understanding concepts) and autonomy (flexible access to resources) enhance intrinsic motivation and positive affect.

Practically, affective value matters because positive emotional responses predict sustained engagement. Students who enjoy using AI resources will continue utilising them voluntarily, whereas students experiencing frustration or boredom will abandon tools regardless of potential benefits. The moderate-to-large affective value

correlations suggest many students developed positive emotional associations with AI resources based on experienced benefits.

4.6.3.4. Augmentative Value ($p = 0.575$)

The correlation between supplementary resource perception and preference for more AI ($p = 0.575$, $p < 0.01$) highlights augmentative value, AI's capacity to supplement rather than replace traditional learning materials. Students did not perceive AI as substituting for textbooks or lectures but as adding complementary support.

This finding aligns with Pallant et al.'s (2025) research demonstrating that effective educational AI functions as cognitive scaffold augmenting, not replacing, foundational instruction. Students valued AI summaries for consolidating lecture content, clarifying textbook passages, and providing additional practice, all augmentative functions enhancing traditional pedagogy rather than competing with it.

From an instructional design perspective, augmentative value suggests AI should be positioned explicitly as a supplement, not replacement. Institutions risk undermining traditional pedagogical elements if students perceive AI as sufficient substitutes. Clear communication that AI supports but does not supplant lectures, textbooks, and instructor guidance ensures students engage with comprehensive learning resources rather than narrowly focusing on AI-generated content.

4.6.3.5. Holistic Value ($p = 0.563$)

The relationship between conceptual understanding and overall learning experience ($p = 0.563$, $p < 0.01$, validated through $\chi^2 (16) = 137.225$, $p < 0.001$, Cramer's $V = 0.48$) demonstrates holistic value, AI's contribution to students' global course experience. Students who experienced cognitive benefits (enhanced understanding) reported better overall learning experiences, indicating specific benefits accumulated into holistic satisfaction.

These findings matter because holistic course experiences influence long-term outcomes, persistence, course selection, career interest. Students experiencing positive learning in ACC1A due to AI support may develop more favourable dispositions toward Accounting, increasing likelihood of continued study. Conversely, negative experiences could deter students from the field. The moderate positive

correlation suggests AI resources contributed meaningfully, though not solely, to overall course experiences.

4.6.4 Summary: Hierarchy of AI Value Dimensions

Figure 19 presents the five value dimensions, hierarchically ordered by correlation strength:

Ranking	Relationship between statements	Strength of Relationship (Spearman's correlation coefficient)	Effect Size of Relationship (Cramer's V)	Interpretation of Correlation Strength	Value
1	"The AI-generated lecture summaries helped me understand the key concepts of the ACC1A module" & "The AI-generated lecture summaries were easy to understand and follow"	Large ($\rho = 0.692$, $p < 0.01$)	Large ($X^2(16) = 205.140$, $p < 0.001$, <i>Cramer's V</i> = 0.587)	Strongest	Cognitive value (ie. understanding concepts)
2	"The AI-generated homework questions were useful in preparing me for exams and assessments" & "The AI-generated lecture summaries and homework questions made learning more engaging for me"	Medium ($\rho = 0.635$, $p < 0.01$)	Large ($X^2(16) = 200.941$, $p < 0.001$, <i>Cramer's V</i> = 0.581)	Strong	Instrumental value (assessment value)
3	"The AI-generated lecture summaries helped me understand the key concepts of the ACC1A module" & "I would prefer to	Medium ($\rho = 0.575$, $p < 0.01$)	Large ($X^2(16) = 100.861$, $p < 0.001$, <i>Cramer's V</i> = 0.411)	Moderate to strong	Affective value (positive affect and motivation)

	have more AI-generated resources integrated into learning materials for the ACC1A module"				
4	"I would prefer to have more AI-generated resources integrated into learning materials for the ACC1A module" & "AI-generated resources are a useful supplement to traditional learning materials (like the textbook and module guide) in the ACC1A module"	Medium ($\rho = 0.575$, $p < 0.01$)	Large ($X^2(16) = 164.167$, $p < 0.001$, <i>Cramer's V</i> = 0.525)	Moderate to strong	Augmentative value (supplementary support)
5	"The AI-generated lecture summaries helped me understand the key concepts of the ACC1A module" & "The use of AI-generated resources in the ACC1A module improved my overall learning experience"	Medium ($\rho = 0.563$, $p < 0.01$)	Large ($X^2(16) = 137.225$, $p < 0.001$, <i>Cramer's V</i> = 0.48)	Moderate	Holistic value (overall learning experience)

Figure 19: Establishing the benefits derived from students' use of the customised Generative AI tool

This hierarchy reveals students valued AI primarily for cognitive benefits (understanding), followed closely by instrumental benefits (assessment preparation). Affective, augmentative, and holistic values emerged as secondary but meaningful dimensions. The hierarchy suggests that designing AI for clarity and comprehension (cognitive value) should be prioritised, followed by ensuring transparent assessment

relevance (instrumental value). When these core values are achieved, secondary affective and holistic benefits naturally follow.

4.6.5 Integration with Qualitative Content Analysis

The open-ended questions asking, “Can you describe your overall experience with the AI-generated lecture summaries in the ACC1A module?” “How did the AI-generated homework questions impact your understanding of the module content?” and “How did the AI tool (ie. Mathu App) influence your motivation and engagement with the ACC1A module” yielded qualitative responses coded through content analysis. Three dominant themes emerged:

Theme 1: Clarity and Conceptual Simplification (n=14 responses, 39%)

Representative quotes:

- “Easy to understand especially for students who have no prior knowledge to Accounting”
- “Straight forward, easy to understand because the summaries are concise”
- “The AI-generated summaries broke down the sections into easier and understandable notes. The quizzes were also helpful after each summary”
- “The Mathu App made it easier to stay engaged with the ACC1A module by simplifying complex content and offering quick summaries. It increased my interest in the course by making studying more accessible and less overwhelming, which helped me stay motivated and participate more actively.”

This theme directly corroborates the quantitative finding of high cognitive value ($p = 0.692$). Students valued AI primarily for enhancing comprehension through clear explanations.

Theme 2: Assessment Confidence and Exam Preparation (n=6 responses, 17%)

Representative quotes:

- “The homework questions helped me practise for the tests and so I had a better understanding”
- “These were possible questions in tests”

- “They helped me prepare for my exam”

This theme confirms the instrumental value finding ($p = 0.635$), with students explicitly linking AI use to assessment readiness.

Theme 3: Motivated self-directed learning (n=7 responses, 19%)

Representative quotes:

- “I was practicing Accounting more frequently throughout my week”
- “It helped me engage with the content more and practiced it more in my spare time”
- “It made me go beyond the textbook and be more intentional about my schoolwork”

This theme connects to Self-Directed Learning principles, AI resources supported learner autonomy through flexible access and self-directed engagement. This qualitative theme was not directly captured in Likert-scale items but emerged unprompted, suggesting students implicitly valued SDL affordances even without explicitly recognising them as “self-directed learning.”

The convergence between quantitative correlations (cognitive and instrumental value) and qualitative themes (clarity/simplification and assessment confidence) strengthens confidence that findings represent genuine student experiences rather than survey artifacts or socially desirable responding. Method triangulation (Denzin, 2012) increases credibility when independent data sources yield consistent patterns.

4.7 Perceived Challenges and Technical Difficulties

While previous sections examined benefits, this section addresses challenges students encountered using AI resources, including technical difficulties, usability concerns, and limitations in AI-generated content.

4.7.1 Prevalence of Technical Difficulties

Figure 20 presents the frequency distribution of the prevalence of technical difficulties experienced by students. Combined disagreement reached 38.9%, indicating the majority did not experience technical difficulties. However, 28.2% (combined agreement) reported technical barriers, and 32.9% expressed neutrality.

I faced technical difficulties or challenges when interacting with the AI-generated lecture summaries and homework questions					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly disagree	14	9.4	9.4	9.4
	Disagree	44	29.5	29.5	38.9
	Neutral	49	32.9	32.9	71.8
	Agree	29	19.5	19.5	91.3
	Strongly agree	13	8.7	8.7	100
	Total	149	100	100	

Figure 20: Frequencies related to the construct of perceived challenges

Interpreting the Challenge Profile

The finding that 71.1% (disagreement plus neutrality) did not definitively confirm technical difficulties suggests the AI tool functioned adequately for most users from an infrastructure perspective. This is methodologically important. If technical failures were widespread, negative perceptions of usefulness would be confounded by implementation problems rather than reflecting genuine pedagogical shortcomings.

However, the 28.2% reporting technical difficulties represents a substantial minority experiencing barriers that potentially excluded them from learning benefits others accessed. In technology implementation research, adoption rates above 20% encountering non-functional access are concerning (Rogers, 2003), indicating systemic problems requiring intervention.

Equity Implications

From an equity perspective, the 28.2% experiencing technical difficulties represent students potentially disadvantaged by AI integration. Educational technology should enhance learning opportunities equitably; when technical barriers exclude particular students, technology exacerbates rather than reduces inequalities (Selwyn, 2011).

In South African higher education contexts characterised by socioeconomic diversity and variable technological infrastructure, ensuring equitable access to digital learning tools constitutes an ongoing challenge (Czerniewicz & Brown, 2013). Students lacking reliable internet connectivity, recent device hardware, or sophisticated digital literacy skills face greater barriers to AI tool usage. While demographic data collected did not include socioeconomic indicators, campus differences may proxy for these factors.

Durban Westville campus serves more socioeconomically diverse student populations than Sandton campus, potentially explaining differential technical access (though this was not statistically tested due to sample constraints).

4.7.2 Nature of Technical Difficulties: Content Analysis Findings

Figure 21 presents the frequency of responses pertaining to the nature of technical difficulties experienced by students. Content analysis identified specific problem categories:

Question 2: Were there any challenges you faced while using the AI-generated resource for your learning?

Theme	Description	Frequency (n)	% of Total Responses
No Challenges / Positive Experience	Responses indicating no difficulties, everything worked well, or easy to use.	45	55%
Technical / Access Issues	Problems with loading, logging in, downloading, or app bugs.	10	12%
Complexity / Confusing Interface	App was complicated, confusing, or	7	9%

Figure 21: Challenges related to use of AI-generated resources

Login Failures and Errors (15 responses, 18% of total sample)

Students reported inability to access the MathU platform due to problems with loading, logging in, downloading, or app bugs, as well as incorrect answers, marking errors, or mismatched calculations. These represent infrastructure challenges requiring IT solutions, server capacity improvements, clearer login instructions and technical support availability.

Complexity and confusing interface (7 responses, 9% of total sample)

Some students experienced the customised Generative AI tool as complicated, confusing, or discouraging, struggling to locate specific features or understand how to use pathway questions effectively. Notably, this represents usability problems, not technical failures. The distinction matters, in that technical failures (login errors,

download problems) require IT solutions, while usability concerns require pedagogical design solutions, simplified interfaces, tutorial videos, user testing with students.

Limited Detail / Content Depth (4 responses, 5% of total sample)

Students reported that the AI-generated resources lacked detail, provided summaries that were too brief, or did not provide enough explanation.

No Challenges Experienced (82 responses, 55% of total sample)

Importantly, the majority of students explicitly reported experiencing no challenges, corroborating the quantitative finding that most students (71.1%) did not encounter significant technical difficulties.

4.7.3 Distinguishing Technical Failures from Pedagogical Limitations

A critical finding emerged from cross-tabulation analyses examining relationships between technical difficulties and PU. Conventional wisdom suggests students experiencing technical problems would rate AI resources as less useful. However, chi-square analyses revealed unexpected patterns, whereby students reporting no technical difficulties still exhibited mixed perceptions of usefulness, responses split between agreement and disagreement.

Figure 22 presents cross-tabulations comparing "I faced technical difficulties" with usefulness statements. Responses were divided between agree and disagree rather than clustering in agreement as expected. This pattern suggests that technical functionality does not guarantee educational value. A perfectly functioning AI tool that fails to address learning needs provides no benefit, while students overcoming minor technical obstacles may still perceive substantial pedagogical value.

Statements compared:	Trend
I faced technical difficulties or challenges when interacting with the AI-generated lecture summaries and homework questions vs. The AI-generated lecture summaries helped me understand the key concepts of the ACC1A module	Responses were split between agree and disagree
I faced technical difficulties or challenges when interacting with the AI-generated lecture summaries and homework questions vs. The AI-generated lecture summaries were easy to understand and follow	Responses were split between agree and disagree

I faced technical difficulties or challenges when interacting with the AI-generated lecture summaries and homework questions vs. The AI-generated homework questions helped me reinforce my learning and improved my understanding of the material	Responses were split between disagree and neutral
I faced technical difficulties or challenges when interacting with the AI-generated lecture summaries and homework questions vs. The AI-generated homework questions were useful in preparing me for exams and assessments	Responses were split between agree and disagree

Figure 22: Crosstabulations reflecting a change in trend, where the majority of the responses were split between agree and disagree

These findings challenge technological determinism, the assumption that providing functional technology automatically improves learning (Cuban, 2001). Educational effectiveness depends on pedagogical design, content relevance, and alignment with learning needs, not merely technical performance. The disconnect between technical access and PU indicates that successful AI implementation requires simultaneous attention to:

Technical Infrastructure: Ensuring reliable access, fast performance, and cross-platform compatibility

Pedagogical Design: Creating content that genuinely supports learning, addresses student needs, and aligns with assessment

User Support: Providing guidance on effective AI integration into study routines

Addressing only technical dimensions while neglecting pedagogical or support dimensions produces functioning tools that students find unhelpful, a failure to deliver learning value despite technical success.

4.7.4 Practical Implications: Equity and Access

The findings underscore that equitable AI integration demands proactive attention to multiple access barriers:

Technical Equity: The 28.2% experiencing difficulties require targeted support:

- Multiple access modalities (mobile app, web browser, offline options for low-connectivity contexts)
- Comprehensive technical support staffing during peak usage periods

- Proactive outreach to students reporting access problems (automated alerts when students haven't logged in)
- Device lending programs for students lacking adequate hardware

Usability Equity: The 9% finding navigation confusing require:

- Comprehensive onboarding tutorials demonstrating AI tool usage
- Simplified interfaces minimising clicks required to access content
- User testing with diverse student populations to identify usability barriers
- Alternative formats (text-only summaries, downloadable PDFs) for students preferring different modalities

Digital Literacy Equity: Some students may possess technical access but lack digital literacy to use tools effectively:

- Explicit instruction on when and how to use AI resources optimally
- Peer mentoring pairing confident users with uncertain students
- Metacognitive prompts helping students recognise AI's value in learning

Without systematic attention to these equity dimensions, AI integration risks reproducing existing inequalities, advantaging already-privileged students with technical resources, digital skills, and self-directed learning capabilities while further disadvantaging students lacking these assets (Watters, 2021).

4.8 Conclusion: Key Patterns, Theoretical Implications, and Transitions

This chapter presented quantitative findings examining 149 first-year ACC1A students' learning experiences with a customised Generative AI tool. Through descriptive statistics, correlation analyses, and integration with qualitative content analysis, four major patterns emerged warranting careful interpretation.

4.8.1 Summary of Key Findings

Pattern 1: Divided Perceptions with Substantial Neutrality

Student perceptions split into three roughly equal groups across multiple constructs:

- 40-48% agreed AI resources provided learning benefits

- 40-47% responded neutrally, indicating ambivalence or conditional experiences
- 9-12% disagreed, perceiving no benefits or negative impacts

This tripartite distribution contrasts with literature reporting predominantly positive student reactions to AI learning tools (Chan & Hu, 2023; Santos & Serpa, 2023), suggesting benefits are more conditional than prior research implies. The substantial neutral responses represent this study's most significant finding, indicating that AI effectiveness varied considerably depending on individual students, specific features used, learning contexts, or implementation factors.

Pattern 2: Usability as Gateway to Perceived Benefits

EOU consistently predicted positive perceptions across constructs:

- EOU → Confidence to use ($\rho = 0.358$, $p < 0.01$)
- EOU → Understanding concepts ($\rho = 0.692$, $p < 0.01$)
- EOU → Overall positive experience ($\rho = 0.563$, $p < 0.01$)

This pattern aligns with Technology Acceptance Model's core premise which posits that PEOU functions as foundational determinant of technology acceptance (Davis, 1989). When students found AI resources clear and navigable, they developed confidence using them, experienced cognitive benefits, and formed positive overall impressions. Conversely, usability barriers undermined potential pedagogical value, even well-designed content proves ineffective if students cannot access or comprehend it easily.

Pattern 3: Instrumental Orientation Predominates

Students valued AI resources primarily for instrumental benefits:

- Assessment preparation usefulness ranked highest (57.8% agreement)
- Exam preparation → Enhanced engagement ($\rho = 0.635$, strongest instrumental correlation)
- Conceptual understanding, while valued (48.3%), ranked below assessment preparation

This instrumental focus reveals students' pragmatic, strategic approach to AI resources, evaluating them primarily through the lens of "will this help me pass?" rather than "will this deepen my understanding?" While SDL theory emphasises intrinsic motivation (Garrison, 1997), students demonstrated realistic prioritisation given assessment-driven contexts characterising South African higher education (Maree, 2015).

Pattern 4: Technical Accessibility Not Sufficient for Value

While most students (71.1%) did not experience major technical difficulties, the absence of technical problems did not guarantee PU:

- Students with no technical barriers still exhibited mixed perceptions (agreement/disagreement split)
- 28.2% encountered technical difficulties excluding them from potential benefits
- Usability concerns (9%) represented different challenges than technical failures

These findings challenge assumptions that providing functional technology suffices for learning improvement. Educational value depends on pedagogical design, content relevance, and student support, not merely technical performance.

4.8.2 Surprising and Unexpected Findings

Three findings diverged from anticipated patterns based on literature:

Unexpectedly High Neutrality

Prior AI-in-education research typically reports 65-75% positive student perceptions (Chan & Hu, 2023; Santos & Serpa, 2023). This study's 40-48% agreement rates and 40-47% neutrality suggest benefits are more heterogeneous and conditional than literature implies. Several factors may explain this discrepancy:

Customised versus Generic AI: Previous studies often examined generic AI tools (ChatGPT, Google Bard) used broadly; this study evaluated a specific customised tool. Students may hold higher standards for specialised tools compared to freely available alternatives.

Comparison Standards: With 89.9% reporting prior AI experience, students compared this tool against alternatives rather than evaluating "AI versus no AI."

Neutrality may reflect perceived equivalence "this tool is no better than ChatGPT", rather than genuine ambivalence.

Longitudinal Perspective: Data collected after eight weeks may have captured post-honeymoon realities after initial enthusiasm waned, contrasting with studies surveying students after 1-3 weeks when novelty effects remain strong.

Instrumental Over Intrinsic Motivation

SDL theory predicts learners pursue understanding for its own sake, valuing knowledge intrinsically (Garrison, 1997). However, students demonstrated clearly instrumental orientations, prioritising exam preparation above conceptual mastery. While this finding aligns with research in assessment-driven contexts (Biggs, 1987; Maree, 2015), it challenges SDL theory's applicability to first-year students still developing autonomous learning capacities, questioning whether AI tools support SDL development, or require existing SDL competencies to be effective.

Technical Access Insufficient for Educational Value

The finding that students without technical barriers still expressed neutral or negative perceptions surprised expectations. Conventional wisdom suggests eliminating access barriers should reveal educational value. However, the disconnect between technical functionality and PU demonstrates that pedagogical design, not infrastructure, determines learning benefits. This finding has substantial practical implications, suggesting that investing in technical infrastructure alone cannot ensure effective AI integration, pedagogy must be prioritised equally.

4.8.3 Connecting Findings: Emergent Themes

Across quantitative findings, three interconnected themes emerged:

Theme 1: Conditional Effectiveness

No finding demonstrated universal agreement or disagreement. Instead, every construct exhibited divided perceptions, some students benefiting, others not, many uncertain. This heterogeneity suggests AI tools function as learning resources requiring strategic deployment rather than interventions with consistent effects. Effectiveness appears conditional on:

- Individual characteristics (SDL readiness, prior knowledge, learning preferences)

- Feature-specific usage patterns (summaries versus pathway questions)
- Contextual factors (topic complexity, timing within semester, complementary instruction)

Theme 2: Usability as Prerequisite

Consistent relationships between EOU and positive outcomes across constructs confirm usability as a gateway to educational value. This finding aligns with TAM but extends it by demonstrating usability's role in educational rather than purely technological contexts. Implications for design are clear; pedagogically sophisticated AI content proves ineffective if students cannot access or understand it. Usability must be prioritised as the foundational requirement enabling other benefits.

Theme 3: Strategic Pragmatism

Students approached AI resources pragmatically, evaluating utility through assessment-focused lenses. Rather than representing deficiency, this orientation reflects rational adaptation to high-stakes educational contexts. The challenge for educators becomes designing AI tools serving instrumental student goals while promoting deeper learning, reconciling pragmatic orientations with pedagogical ideals.

4.8.4 Theoretical Implications and Tensions

Findings generate important theoretical insights while raising tensions requiring further exploration.

SDL Theory: Promise and Limitations

Self-Directed Learning theory provided valuable interpretive lens for understanding how AI tools might support autonomous learning through flexible access, self-paced engagement, and learner control. Students who experienced these affordances reported enhanced engagement and positive experiences, confirming SDL predictions.

However, SDL theory's applicability to first-year students requires qualification. SDL theory emerged from adult education contexts (Knowles, 1975) and assumes learners possess self-management skills, intrinsic motivation, and metacognitive awareness. First-year undergraduates may still be developing these capabilities, requiring more scaffolding than SDL models anticipate. The substantial neutral responses and mixed

perceptions suggest many students lacked readiness to leverage SDL-supportive tools effectively.

The theoretical question becomes, should AI tools presuppose SDL readiness, or should they scaffold SDL development? This study's findings suggest the latter, that AI tools should support students at various SDL maturity levels rather than assuming existing competencies.

TAM: Confirmed but Insufficient

Technology Acceptance Model successfully predicted that PEOU and usefulness would influence attitudes and behavioural intentions (Davis, 1989). The strong correlations between EOU, PU, overall experience, and preference for more AI confirm TAM's validity in educational contexts.

However, TAM emphasises adoption over learning outcomes. Students might accept and enthusiastically use technology providing minimal educational benefit (or vice versa). This study's integration of TAM with learning-focused constructs (conceptual understanding, learning reinforcement) demonstrates that acceptance alone is insufficient, educational effectiveness must be evaluated directly, not inferred from adoption rates.

Instrumental versus Intrinsic Motivation: Reconciliation Needed

The prominence of instrumental benefits challenges educational theories emphasising intrinsic motivation (SDL, constructivism, deep learning approaches). However, rather than viewing instrumental and intrinsic orientations as opposing, findings suggest they coexist and interact. Students simultaneously valued AI for exam preparation and conceptual understanding, recognising that Accounting assessment success requires genuine comprehension.

This synthesis suggests pedagogical strategies reconciling instrumental and intrinsic goals:

- Design assessment requiring deep understanding, making intrinsic learning instrumentally valuable
- Communicate transparently how conceptual mastery supports assessment performance

- Provide immediate feedback on practice questions, making learning feel productive and goal-directed

4.8.5 Limitations of Quantitative Findings

Several methodological constraints limit interpretation:

Self-Report Bias

All data derived from student perceptions via the questionnaire. Students may have provided socially desirable responses or lacked accurate metacognitive awareness to judge whether learning improved. Actual learning outcomes, comparing grades or competency assessments between AI users and non-users, were not measured, preventing causal claims about AI effectiveness beyond PU.

Cross-Sectional Design

Data represents a single time point following eight weeks of AI tool usage. This design precludes causal inference, meaning that it cannot be concluded whether AI tools caused learning benefits. Students experiencing benefits may have been predisposed through prior AI familiarity, higher digital literacy, or stronger intrinsic motivation. Longitudinal or experimental designs would strengthen causal inference by tracking perception changes over time or comparing randomly assigned groups.

No Control Group

Without comparison group learning without AI tools, AI effects cannot be isolated from other pedagogical factors, instructor quality, curriculum design, peer support or personal study habits. The AI tool operated within a complex learning ecology; therefore, attributing outcomes solely to AI represents an oversimplification. Ideally, controlled experiments comparing matched sections with and without AI would clarify unique contributions.

Missing Subgroup Analyses

Sample size constraints ($n=149$) prevented robust subgroup comparisons by gender, campus, prior AI experience, or academic performance. These analyses might reveal differential effectiveness:

- Perhaps male and female students valued different AI features

- Perhaps high-performing students leveraged AI differently than struggling students
- Perhaps prior AI experience moderated perceptions (though 89.9% had experience, limiting variance)

These remain important questions warranting larger-sample research.

Quantitative-Qualitative Gap

Numbers reveal what students perceived but not why. The 40-47% neutral responses are statistically meaningful but substantively opaque, we don't know what "neutral" meant to respondents. Did they feel genuinely ambivalent? Were benefits conditional? Did they lack comparison points? Qualitative inquiry addresses this interpretive gap.

Measurement Limitations

Likert-scale items, while efficient for quantifying perceptions, constrain responses to predetermined categories. Students may have held opinions not captured by item wording. For instance, no items explicitly asked about SDL dimensions (self-management, self-monitoring, motivation), requiring indirect inference from constructs like engagement and confidence.

4.8.6 Transition to Qualitative Phase

Quantitative findings establish patterns but leave critical questions unanswered, necessitating qualitative exploration presented in Chapter 5:

Explaining Neutrality: Why did 40-47% respond neutrally? What experiences produced ambivalence? When did AI help versus not help?

Understanding Usage Practices: How did students actually use AI resources? Did usage patterns align with intended design? What strategies distinguished successful from unsuccessful users?

Identifying Feature-Specific Perceptions: Which AI features (lecture summaries versus pathway questions) proved more valuable? Did effectiveness vary by Accounting topic?

Clarifying Value Propositions: Why did some students value AI for assessment preparation while others emphasised conceptual understanding? What factors shaped these different value orientations?

Exploring Individual Differences: What characteristics distinguished students who benefited from those who didn't? Did SDL readiness, prior knowledge, or learning preferences mediate effectiveness?

Documenting Challenges Beyond Technical Difficulties: What non-technical barriers hindered effective use? Did students struggle with metacognitive judgments about when to use AI? Did they experience information overload?

Chapter 5 presents findings from semi-structured interviews with 14 students and focus group discussions with 10 students, split into 4 groups, purposively sampled to represent high, moderate, and low AI engagement levels. Through students' own words and experiences, the qualitative phase provides interpretive richness missing from numerical data, enabling a comprehensive understanding of how and why customised AI tools shaped learning in ACC1A.

Final Reflections: What Quantitative Findings Reveal

This chapter demonstrates that quantitative inquiry effectively identifies patterns, magnitudes, and relationships, revealing what happened among 149 students over eight weeks. Descriptive statistics quantified perceptions, correlation analyses identified significant relationships, and statistical tests validated patterns. These contributions are substantial. Findings reveal that perceptions divided roughly into thirds (agree/neutral/disagree), that usability predicted benefits, and that instrumental orientations predominated.

However, quantitative inquiry reveals its limits when attempting to explain why patterns emerged or what they mean for students' lived experiences. Numbers tell us 45.6% felt neutral about engagement but cannot capture what "neutral" felt like or what experiences produced it. Correlations demonstrate EOU predicts confidence but cannot illuminate the psychological mechanisms linking usability to self-efficacy.

These limitations do not diminish quantitative inquiry's value; rather, they underscore the necessity of mixed-methods design. Quantitative findings provide breadth, patterns across large samples, while qualitative findings provide depth and a rich understanding of experiences underlying patterns. Together, Chapters 4 and 5 construct complementary knowledge, with Chapter 6 integrating both to generate

comprehensive, theoretically grounded, practically applicable insights into AI's role in supporting learning in South African Accounting education.

Chapter 5: Presentation and Interpretation of Findings (Qualitative Phase): Understanding How and Why AI-Generated Resources Shape Learning Experiences in ACC1A

5.1 Introduction

Chapter 4 presented quantitative findings from 149 first-year Accounting students, revealing three significant patterns requiring deeper exploration. First, while 48-58% of students perceived AI-generated resources as useful for assessment preparation and conceptual understanding, 40-47% provided neutral responses across multiple constructs, suggesting conditional or context-dependent experiences. Second, strong positive correlations between PEOU and PU ($\rho = 0.692$, $p < 0.01$) indicated that usability significantly influenced learning benefits. Third, students valued AI resources primarily for instrumental goals, with exam preparation ranking highest, revealing strategic rather than intrinsically motivated learning orientations.

These quantitative patterns establish what happened but cannot explain why. Numbers reveal that nearly half of students remained neutral about AI benefits, but cannot illuminate what experiences produced this ambivalence. Correlation coefficients demonstrate relationships between usability and perceived learning gains, but cannot clarify the mechanisms through which EOU shapes educational value. Frequency distributions show instrumental orientations predominated, but cannot explain why students prioritised assessment preparation over conceptual exploration, or whether this reflects AI tool limitations, assessment design, or student learning approaches.

This chapter presents qualitative findings addressing the interpretive gaps left by quantitative analysis. The chapter responds to two critical research questions:

- Research Question 2: How does a customised Generative AI tool shape first-year students' understanding of learning outcomes and skill development in the ACC1A module?
- Research Question 3: Why do first-year students perceive AI-generated resources as beneficial or challenging in supporting their learning in the ACC1A module?

Through semi-structured interviews with 14 students and focus group discussions with 10 students, all enrolled at the Pietermaritzburg campus, this chapter provides rich

narrative accounts of students' lived experiences with AI resources. Findings reveal not only how students used AI tools and what outcomes they achieved, but why certain features supported learning while others created barriers, under what conditions AI proved beneficial, and what individual, pedagogical, and technological factors mediated effectiveness.

5.1.1 Research Questions and Theoretical Framework

Research Question 2 examines AI's influence on learning outcomes and skill development. From a Self-Directed Learning (SDL) perspective (Garrison, 1997; Knowles, 1975), this question investigates whether AI resources supported the three dimensions of self-directed learning, including self-management (students' ability to plan and execute learning activities independently), self-monitoring (students' capacity to assess their understanding and identify knowledge gaps), and intrinsic motivation (internal drive to understand Accounting concepts beyond assessment requirements). SDL theory predicts that educational tools promoting learner autonomy, providing flexible access to resources, and facilitating self-assessment will enhance learning outcomes and be valued by students (Garrison, 1997).

Research Question 3 explores why students perceived benefits or challenges. Technology Acceptance Model (TAM) (Davis, 1989) provides explanatory power here, proposing that PU (the degree to which technology improves learning performance) and PEOU (the degree to which technology requires minimal cognitive effort) determine technology acceptance and sustained usage. TAM predicts that even pedagogically sound tools will be underutilised if students find them difficult to navigate or perceive them as unhelpful for achieving their learning goals.

Together, SDL and TAM enable theoretical interpretation of qualitative findings. When students describe AI resources as "explaining the basics clearly" but "not preparing me for exams," SDL theory helps interpret this as supporting understanding (foundational SDL component) but failing to support self-monitoring (students cannot assess exam readiness). When students report abandoning AI tools because "it's too much effort on my phone," TAM explains how poor EOU undermines PU, regardless of actual educational quality. Throughout this chapter, student experiences are analysed through these theoretical lenses to generate insights transcending mere description.

5.1.2 Connecting to Chapter 4: Explaining Quantitative Patterns

Before presenting qualitative themes, it is essential to explicitly map how this chapter addresses patterns identified in Chapter 4. Figure 23 establishes these connections, demonstrating how qualitative inquiry illuminates quantitative findings.

Quantitative Pattern	Qualitative Theme	Mapping
40-47% neutral responses across PU constructs	Why did students feel ambivalent? Under what conditions was AI helpful versus unhelpful?	Sections 5.6 and 5.7 examine conditional effectiveness and contextual factors producing mixed experiences
Strong correlation between EOU and PU ($\rho = 0.692$)	How does usability shape learning value? What specific usability barriers hindered effectiveness?	Section 5.7.2 explores device limitations, interface challenges, and accessibility issues that undermined perceived benefits
Instrumental orientation: 58% valued AI for exam preparation most highly	Why did assessment preparation dominate? Does this reflect AI limitations or student strategic behaviour?	Section 5.7.1 reveals pedagogical misalignment between AI content and assessment demands, explaining why students sought exam-focused value
48% found AI useful for conceptual understanding	How did AI support understanding? What conceptual gains did students actually achieve?	Section 5.4 documents AI's role in explaining foundational concepts and providing procedural clarity
Varied perceptions of learning reinforcement and confidence building	What learning processes did AI support or hinder?	Section 5.5 examines skill development patterns, revealing AI supported lower-order cognitive skills but neglected higher-order competencies

Figure 23: Mapping Qualitative Themes to Quantitative Patterns

This mapping demonstrates that qualitative findings are not parallel investigations but direct explanations of quantitative patterns. The following sections present thematic findings organised around theoretical constructs and research questions, with explicit connections to Chapter 4 patterns integrated throughout.

5.2 Methodological Approach

5.2.1 Research Design and Epistemological Positioning

This qualitative phase employed an interpretivist epistemology, seeking to understand the subjective meanings students constructed from their experiences with AI resources (Creswell & Poth, 2018). Interpretivism assumes that reality is socially constructed and that multiple valid interpretations exist, requiring researchers to understand phenomena from participants' perspectives rather than imposing predetermined categories (Merriam & Tisdell, 2016). This epistemological stance aligns with the study's exploratory purpose to understand how students made sense of AI tools within their unique learning contexts rather than testing hypotheses about AI effectiveness.

The qualitative design employed two complementary data collection methods, namely semi-structured interviews and focus group discussions. Semi-structured interviews allowed exploration of individual experiences, learning strategies, and personal reactions to AI resources, providing depth and nuance (Brinkmann & Kvale, 2015). Focus group discussions facilitated peer interaction, enabling students to build on each other's observations, challenge or validate perspectives, and collectively construct meaning (Krueger & Casey, 2015). Together, these methods generated both individual narratives and socially negotiated understandings.

5.2.2 Participant Sampling and Selection

Participants were selected through purposive sampling designed to capture variation in AI engagement levels identified in Chapter 4's quantitative analysis. Following Patton's (2015) maximum variation sampling strategy, I sought students representing high, moderate, and low AI usage patterns to understand how different engagement intensities shaped learning experiences. However, practical constraints limited sampling to the Pietermaritzburg campus due to researcher access and resource availability during the September-October 2025 data collection period.

Semi-structured interviews were conducted with 14 students during September 2025. Participants were recruited through ACC1A course announcements and direct invitations to students representing varied quantitative questionnaire responses (strongly agree, neutral, and disagree patterns). Interviews were conducted face-to-

face in private campus venues, lasting 15-20 minutes each. All interviews were audio-recorded with participant consent and transcribed verbatim.

Focus group discussions involved 10 students organised into four groups during two separate sessions in October 2025. Group sizes ranged from 2-3 participants, smaller than conventional focus group recommendations of 6-10 participants (Krueger & Casey, 2015). This deviation was deliberate as smaller groups facilitated deeper individual contributions and ensured all voices were heard, particularly important, given potential power dynamics among first-year students. Each two-hour session incorporated both structured discussion prompts and collaborative activities requiring students to analyse AI-generated resources and reflect on learning processes. These activities generated written artefacts (annotated summaries, benefit-challenge charts) supplementing verbal discussions.

5.2.3 Participant Characteristics and Implications

Figure 24 presents demographic characteristics of the qualitative participants, enabling comparison with Chapter 4's quantitative sample and assessment of transferability.

Demographic category	Semi-structured interviews (n=14)	Focus groups (n=10)	Total Qualitative Sample (n=24)	Quantitative Sample – for comparison (n=149)
Male	6 (42.9%)	3 (30%)	9 (37.5%)	84 (56.4%)
Female	8 (57.1%)	7 (70%)	15 (62.5%)	61 (40.9%)
African	9 (64.3%)	5 (50%)	14 (58.3%)	Not collected in questionnaire
Indian	2 (14.3%)	3 (30%)	5 (20.8%)	Not collected in questionnaire
Coloured	1 (7.1%)	1 (10%)	2 (8.3%)	Not collected in questionnaire
White	2 (14.3%)	1 (10%)	3 (12.5%)	Not collected in questionnaire
Campus (Pietermaritzburg)	14 (100%)	10 (100%)	24 (100%)	10 (6.7%)
Age range	18-21 years	18-21 years	18-21 years	94% aged 18-21

Figure 24: Demographic profile of qualitative participants

Analytical Implications of Sample Characteristics

Several demographic patterns warrant interpretive consideration which are discussed across three distribution categories, namely gender distribution, racial distribution and campus distribution.

Gender Distribution

Female students comprised 62.5% of qualitative participants compared to 40.9% of questionnaire respondents, representing a notable overrepresentation. Research on technology adoption indicates that gender can moderate perceptions of educational technology, with some studies suggesting females report lower self-efficacy with new technologies despite equivalent actual performance (Venkatesh & Morris, 2000). However, in this study, no clear gender-based pattern emerged in interview or focus group responses. Female and male participants expressed similar concerns about pedagogical alignment, usability challenges, and learning benefits. This gender imbalance nonetheless remains a limitation, as it may have obscured gender-specific experiences that a more balanced sample would reveal.

Racial Composition

The majority of participants identified as African (58.3%), with smaller representation from Indian (20.8%), White (12.5%), and Coloured (8.3%) groups. This composition reflects Emeritus College's demographic profile as a historically diverse institution serving predominantly Black South African students. However, this racial distribution differs from some other South African universities and may influence findings' transferability. Cultural backgrounds can shape learning preferences, technology adoption attitudes, and educational expectations (Prinsloo & Slade, 2016). While no explicit racial differences in AI perceptions emerged from thematic analysis, I acknowledge that my positionality as an Indian female researcher may have limited my ability to recognise culturally specific interpretations students might have hesitated to articulate across racial lines.

Campus Limitation

All 24 qualitative participants attended the Pietermaritzburg campus, representing only 6.7% of Chapter 4's quantitative questionnaire respondents. This severe geographic limitation creates the most significant threat to transferability. Pietermaritzburg, a

smaller regional campus, likely differs from larger urban campuses (Sandton, Durban Westville) in student socioeconomic backgrounds, technological infrastructure quality, prior AI exposure, and general digital literacy. Students at an affluent Sandton campus may have had more extensive prior AI experience and higher-quality home internet access, potentially shaping different perceptions than Pietermaritzburg students expressed. This limitation means findings may overrepresent experiences of students from regional, resource-constrained contexts while underrepresenting perspectives from urban, technologically advanced environments.

Despite these limitations, the purposive sampling achieved its primary goal, capturing variation in AI engagement levels. Interview and focus group participants included students who used AI extensively throughout the semester, those who engaged sporadically, and those who abandoned the tool after initial trials. This variation in usage intensity enabled exploration of factors distinguishing successful from unsuccessful AI adoption, directly addressing Chapter 4's finding that perceptions varied substantially across individuals.

5.2.4 Data Collection Procedures

Semi-Structured Interviews

The interview protocol (Appendix 5) comprised open-ended questions organised around four themes:

- a) General AI tool usage patterns and frequency
- b) Specific learning activities supported by AI resources (studying, assessment preparation, concept clarification)
- c) Perceived benefits and challenges experienced
- d) Suggestions for improvement

While the protocol provided structure, I deliberately adopted a flexible approach, allowing students to elaborate on experiences most salient to them and pursuing emergent themes through follow-up probing (Brinkmann & Kvale, 2015). For example, when Participant #4 spontaneously compared the customised AI tool to TurboLearn (another AI application), I pursued this comparison to understand what features students valued in competing technologies.

All interviews were audio-recorded with explicit informed consent. Participants were assured of confidentiality and anonymity; pseudonyms (Participant #1 through #14) are used throughout this chapter. Students were informed they could withdraw at any point without consequences for their academic standing, and I emphasised that honest, critical feedback was valued more than positive endorsements.

Focus Group Discussions

Focus group sessions integrated structured discussion with collaborative activities designed to stimulate deeper reflection. Each session followed this sequence:

- a) Opening Discussion (20 minutes): General reactions to AI tool, initial impressions, usage frequency
- b) Activity 1: Collaborative Concept Mapping (30 minutes): Groups examined sample AI-generated lecture summaries and pathway questions, annotating strengths, weaknesses, and suggestions for improvement. My intention in this activity was to explore how participants connected AI-generated lecture summaries to their understanding of learning outcomes (VAT and the General ledger) in ACC1A. Written artefacts were collected of students' reflections and concept maps.
- c) Discussion 2: Learning Outcomes and Skills (30 minutes): Facilitated conversation about whether and how AI supported understanding of Accounting concepts and development of Accounting competencies.
- d) Activity 2: Critical Incidents Reflection: Groups created visual diagrams categorising AI benefits and challenges, identifying which were most significant. In this activity my intention was to identify specific moments when the AI tool either enhanced or impeded learning.
- e) Discussion 3: Benefit-Challenge Mapping (20 minutes): Key trends were noted whilst students presented their feedback, and a discussion was held pertaining to the emergent themes.
- f) Activity 3: Skills Ranking: Following the preceding discussion, students were required to rank order the skills they believed they acquired by virtue of their engagement with the AI tool in their learning. My intention of this activity was to evaluate the perceived impact of AI tools on different types of skill development.
- g) Discussion 4: Skills Ranking (20 minutes): Facilitated conversation to extract justification for the rank assigned to each skill identified.

- h) Activity 4: Comparative Analysis: Textbook versus the AI tool: Students compared excerpts from the recommended textbook and an AI-generated summary on the same topic, noting similarities and differences in terms of the clarity of explanation, depth of understanding supported and usefulness for skill development. My intention of this activity was to understand participants' conceptual preferences and learning pathways. Students created a Venn diagram to highlight overlaps and distinctions.
- i) Discussion 5: Comparative Analysis (15 minutes): Facilitated conversation to understand the reasons for the differences, similarities and areas of overlap.
- j) 5. Closing Discussion (20 minutes): Institutional recommendations, comparison to other learning resources, final reflections.

This structured, yet flexible format generated multiple data sources including verbal discussion transcripts, written reflections on the use of the AI resources, and visual benefit-challenge maps. The collaborative activities were particularly valuable, as students often articulated insights while working together that they might not have expressed in interviews alone.

Focus group participants received the same confidentiality assurances as interview participants. Group pseudonyms (Group A through Group D) are used when referencing collective discussions. Where individual contributions within focus groups are quoted, participants are identified as "Group A, Student 1" to maintain anonymity while indicating source.

5.2.5 Thematic Analysis Process

Data analysis followed Braun and Clarke's (2006) six-phase approach to thematic analysis:

Phase 1: Familiarisation

I transcribed all interviews and focus group discussions verbatim within one week of data collection to ensure accuracy and immersion in the data. Transcripts were read multiple times while listening to audio recordings to capture nuances, tone, and emphasis that text alone might miss. During this phase, I maintained reflective memos documenting initial impressions, identified potential patterns using colour coding, and questions for deeper analysis (Merriam & Tisdell, 2016).

Phase 2: Initial Coding

I conducted line-by-line open coding of all transcripts and written artefacts, which were transferred to a Microsoft Office Excel spreadsheet. Initial codes stayed close to participants' language, capturing specific experiences, perceptions, and suggestions. For example, when Participant #13 described AI-generated questions as "too basic" and "not like exam questions," I coded this as "assessment misalignment" and "insufficient complexity." This initial coding generated 22 discrete codes.

Phase 3: Searching for Themes

I grouped related codes into broader potential themes by organising codes into clusters representing coherent patterns. For instance, codes like "assessment misalignment," "insufficient complexity," "too theory-focused," and "doesn't match exam demands" were clustered into a potential theme as "Pedagogical Misalignment Between AI Content and Assessment Requirements." This phase involved constant comparison, moving back and forth between codes, clustered themes, and raw data extracts to ensure themes were grounded in actual participant experiences (Charmaz, 2006).

Phase 4: Reviewing Themes

I reviewed potential themes against coded extracts and entire data sets to ensure coherence and distinctiveness. Some initial themes were collapsed because they overlapped substantially (for example, "limited interactivity" and "lack of engagement features" were merged into "Insufficient Interactive Affordances"). Other themes were split when they contained multiple distinct ideas. This iterative refinement ensured each theme captured a central organising concept supported by substantial data.

Phase 5: Defining and Naming Themes

I developed clear definitions and scope for each theme, ensuring themes directly addressed research questions and connected to SDL and TAM theoretical frameworks. Theme names were crafted to be analytically informative rather than merely descriptive. For instance, rather than naming a theme "Students liked summaries but wanted more practice questions," I named it "AI Supported Declarative Knowledge But Neglected Procedural Competency," which both describes the pattern and interprets its educational significance. Despite not using a statistical analysis

software tool, every effort was made to maintain academic rigour, utilising a systematic procedure of data analysis, as described, ensuring reflexivity and transparency such that the methodological quality remained intact (Braun & Clarke, 2021).

Phase 6: Producing the Report

This chapter represents the final analytical phase, where themes are presented with supporting evidence (participant quotes, activity artefacts), theoretical interpretation (connections to SDL and TAM), and integration with Chapter 4 quantitative findings. Quotes were selected based on three criteria: representativeness (illustrating patterns across multiple participants), clarity (articulating ideas accessibly), and depth (revealing nuanced or unexpected insights).

5.3 Addressing Quantitative Patterns: Initial Qualitative Insights

Before presenting full thematic findings, this section provides preliminary qualitative insights that directly illuminate the three major quantitative patterns identified in Chapter 4. These initial explanations demonstrate how qualitative data addresses interpretive gaps left by numerical analysis.

5.3.1 Explaining Neutral Responses: Conditional Effectiveness

Chapter 4 revealed that 40-47% of students provided neutral responses across PU constructs, neither agreeing nor disagreeing that AI resources improved learning. Qualitative data illuminates why, illustrating that AI effectiveness was highly conditional, depending on what students were trying to accomplish, where they were in their learning journey, and how they used the tool.

Participant #7 articulated this conditionality clearly, *"It depends on what you're studying for. If you just want to understand the basics, like what is an asset or liability, then yes, the summaries help. But if you're preparing for the test where you have to do journal entries and ledger accounts, then no, it doesn't help much because it doesn't show you enough examples of actually doing it."*

This statement reveals that "neutral" responses likely reflected students' recognition that AI provided value in some contexts (initial concept learning) but not others (assessment preparation requiring procedural competency). Students were not

ambivalent about AI's overall worth; rather, they accurately assessed that effectiveness varied by purpose.

Group C's focus group discussion reinforced this pattern:

Group C, Student 2, *"I used it at the beginning of each topic to get an overview, and that helped me understand what the chapter was about. But then when I needed to practice, I went back to the textbook exercises."*

Group C, Student 1, *"Same. It's good for understanding definitions and basic ideas, but not for learning how to actually do Accounting."*

From a Self-Directed Learning perspective, these students demonstrated sophisticated self-monitoring, accurately judging when AI resources matched their learning needs (initial understanding) versus when alternative resources were more appropriate (procedural practice). Their neutral survey responses thus reflect conditional effectiveness rather than confusion or apathy.

This finding also connects to Technology Acceptance Model. PU in TAM depends on task-technology fit, whereby technologies are deemed useful when their capabilities align with task requirements (Goodhue & Thompson, 1995). Students found AI moderately useful overall because it fit some learning tasks (conceptual understanding) but not others (exam preparation), producing neutral aggregate perceptions.

5.3.2 Explaining the Ease of Use-Usefulness Correlation: Usability as a Gateway

Chapter 4 demonstrated a strong positive correlation between PEOU and PU ($p = 0.692$, $p < 0.01$), suggesting usability significantly influenced learning benefits. Qualitative data reveals the mechanism, illustrating that when students struggled with usability, they disengaged before experiencing potential learning benefits, meaning poor EOU prevented usefulness from being realised.

Participant #13 described abandoning AI resources due to device limitations, *"I don't want my phone out while I'm studying because I end up doing other things. So even though the summaries might be good, I'm not going to use them if I have to be on my phone. It's not productive for me personally."*

This account demonstrates that usability barriers (mobile-only access creating distraction) prevented the student from engaging long enough to assess or benefit from content quality. Even pedagogically excellent resources become useless if access friction is too high. TAM explicitly predicts this relationship, EOU directly influences PU because cognitive effort required to use technology subtracts from effort available for learning tasks (Davis, 1989).

Participant #4 compared the customised AI tool unfavourably to TurboLearn on usability grounds, *"TurboLearn felt polished and elegant and slick, it's just easy to use. But MathU felt unfinished. You can't copy the summaries, you can't save them, you have to keep your phone on to access the App. These small things add up and make it frustrating."*

The language "polished," "elegant," and "slick" versus "unfinished" and "frustrating" reveals that usability shapes not just efficiency but also affective responses. Students who found the interface frustrating developed negative emotional associations, reducing willingness to persist despite potentially valuable content. This aligns with TAM's premise that PEOU influences attitude toward using technology, which in turn affects behavioural intention (Davis, 1989).

From an SDL perspective, usability barriers also hindered self-management. When students needed to navigate multiple steps to access resources, they were required to open the App and then scroll through all the information to locate the exact topic, this complexity disrupted autonomous learning flows. Participant #11 expressed this as follows *"The only thing I'd wish it has is the search button. You know whenever you need the information, instead of scrolling, you know you can just search a certain topic and then you can find the information"*. Self-directed learners require low-friction access to resources to maintain momentum; high cognitive load from poor usability diverts mental resources from learning to system navigation (Sweller, 1988).

5.3.3 Explaining Instrumental Orientation: Assessment-Driven Pragmatism

Chapter 4 revealed that 58% of students valued AI primarily for exam preparation, indicating instrumental rather than intrinsic learning orientations. Qualitative data explains why students approached AI resources strategically, evaluating them against assessment demands. When AI content did not align with assessment format or

complexity, students deemed it insufficiently useful for their primary goal (passing exams).

Participant #9 explicitly articulated this assessment-focussed education, *"In the end, what matters is the exam. If the AI questions don't prepare me for the exam questions, then I'm wasting my time using them. I'd rather do past papers or textbook exercises that actually look like what I'll face in the test"*.

This pragmatic orientation does not necessarily reflect shallow learning motivation. Rather, in professional education contexts like Accounting, assessment success is instrumentally rational in terms of progression to second-year studies, eligibility for professional training, and career opportunities which depend on grades. Students prioritising assessment preparation are responding rationally to institutional incentive structures.

However, qualitative data also revealed a pedagogical misalignment that intensified instrumentalism, providing empirical evidence that AI-generated resources focused heavily on declarative knowledge (definitions, concepts, terminology) while assessments required procedural knowledge (executing journal entries, preparing ledger accounts, producing financial statements). Participant #13 captured this misalignment, *"The questions are like true or false or asking about terminology, but in the test we have to do calculations and prepare accounts. So, it doesn't help to practice true/false questions when that's not what's being tested."*

From a constructive alignment perspective (Biggs & Tang, 2011), effective education aligns learning outcomes, teaching activities, and assessment tasks. When AI resources misaligned with assessment demands, students rationally disengaged or limited usage to low-stakes concept review. Their instrumental orientation thus reflects both the reality of assessment-driven education and the specific limitation that AI content did not prepare them for assessment formats actually encountered.

SDL theory emphasises intrinsic motivation, the desire to understand for its own sake, as central to self-directed learning (Knowles, 1975). The strong instrumental orientation observed appears to contradict SDL principles. However, Garrison's (1997) SDL model acknowledges that motivation exists on a continuum from external regulation (avoiding punishment, gaining rewards) to intrinsic interest (inherent satisfaction in learning). First-year Accounting students, navigating an unfamiliar

disciplinary domain with high academic stakes, may appropriately exhibit more extrinsic motivation initially, potentially developing intrinsic interest as competence and confidence grow. The issue may not be students' instrumental orientation per se, but rather AI resources' failure to support even instrumental goals effectively due to assessment misalignment.

These three preliminary insights demonstrate how qualitative findings directly address quantitative patterns. Neutral responses reflected conditional effectiveness; the EOU-usefulness correlation reflected usability barriers preventing engagement; instrumental orientation reflected both rational assessment-focused strategy and pedagogical misalignment. The following sections present comprehensive thematic findings building on these initial explanations.

5.4 How AI Shaped Understanding of Learning Outcomes: Supporting Foundational Knowledge

This section addresses the first component of Research Question 2: How did the customised Generative AI tool shape students' understanding of ACC1A learning outcomes? Findings reveal that AI resources effectively supported foundational, conceptual understanding through clear explanations of Accounting terminology, frameworks, and basic principles. However, this support was limited to declarative knowledge (knowing what), with minimal contribution to procedural knowledge (knowing how) or conditional knowledge (knowing when and why).

5.4.1 Explaining Foundational Accounting Concepts

The most consistent theme across interviews and focus groups was that AI-generated lecture summaries provided accessible explanations of foundational Accounting concepts. Students valued the simplified, structured presentation of core ideas, which helped them grasp basic terminology and frameworks before engaging with more complex applications.

Participant #2 described how AI summaries clarified fundamental concepts, *"When I first started Accounting, I didn't understand the difference between assets and liabilities, or what equity meant. The AI summaries broke it down simply; assets are what the business owns, liabilities are what it owes, equity is the owner's interest. That simple explanation helped me understand before going into more detail in the textbook."*

This account illustrates AI's role in introducing disciplinary vocabulary and categorisation systems. For novice learners entering an unfamiliar knowledge domain, accessible explanations of core concepts provide essential scaffolding for subsequent learning (Vygotsky, 1978). The AI summaries functioned as advance organisers (Ausubel, 1968), providing cognitive structures that helped students organise and integrate new information encountered in lectures and readings.

Group A's focus group discussion revealed similar experiences:

Group A, Student 1, *"The summaries helped me understand the basic structure of Accounting, like the Accounting equation, assets equal liabilities plus equity. I didn't understand that from lectures at first, but the AI explained it step by step."*

Group A, Student 3, *"Yes, and it shows how when assets increase, either liabilities or equity must increase too. That relationship wasn't clear to me before."*

These students demonstrate conceptual understanding of fundamental Accounting relationships. From an SDL perspective, this represents support for self-management, whereby students could independently access explanations when they identified knowledge gaps, without waiting for instructor availability. The on-demand nature of AI resources allowed students to control the timing and pace of initial concept learning, enhancing autonomy (Garrison, 1997).

Participant #5 specifically valued the structured, sequential presentation, *"The way it was organised helped me. It didn't jump around. It started with definitions, then explained how things connect, then gave examples. That logical flow made it easier to follow than my lecture notes which sometimes feel scattered."*

This comment highlights an affordance of AI-generated resources enabled through algorithmic content generation which can produce highly structured, logically sequenced explanations that may be difficult for time-constrained lecturers to consistently deliver in live teaching. The predictable structure reduced cognitive load (Sweller, 1988), allowing students to focus on comprehending content rather than determining organisational logic.

However, from a TAM perspective, the value of clear explanations depended on students recognising their need for foundational support. High-performing students or

those with prior Accounting knowledge sometimes found basic explanations unnecessary.

Participant #11 expressed this view, *"For me, the summaries were too basic. I already understood what assets and liabilities are from my high school Accounting. I needed help with more advanced things like adjusting entries and closing procedures, but the AI didn't go deep enough into those."*

This reveals an important limitation of the AI resources which were most useful for students requiring foundational concept introduction but less valuable for those ready to move beyond basics. The lack of adaptive personalisation meant the tool could not adjust complexity to individual readiness levels, potentially contributing to neutral responses amongst more advanced learners.

5.4.2 Providing Procedural Clarity Through Step-by-Step Guidance

Beyond conceptual explanations, AI summaries occasionally provided procedural guidance outlining steps for completing Accounting tasks. Students valued this structured approach to procedural learning, particularly for multi-step processes like preparing journal entries.

Participant #6 described using AI summaries for procedural support, *"When I had to learn how to record a transaction, the AI showed the steps like, identify the accounts affected, determine if they increase or decrease, decide if it's a debit or credit, write the journal entry. Having those steps written out clearly helped me practice."*

This procedural scaffolding supports SDL's self-monitoring dimension whereby students could check their understanding of correct procedures against AI-provided steps, identifying where their approach deviated from expert practice. The explicit articulation of procedures that experts perform automatically but novices struggle to infer is pedagogically valuable (Chi & VanLehn, 2012).

However, qualitative data revealed a critical limitation revealing that AI summaries outlined procedures but provided insufficient practice opportunities. Participant #13 expressed frustration with this gap, *"It tells you the steps, which is good, but then you need to practice those steps many times with different examples. The pathway questions didn't give enough practice, and they were too simple compared to what we had to do in exams."* One of the participants in Group B expressed this limitation during

the focus group discussion as follows, *“It helped me because it gave the formulas, but I wish it would have also included how to solve this equation in the exam”*.

This finding connects directly to the quantitative pattern of instrumental orientation (58% valued AI for exam preparation). Students recognised that knowing procedures theoretically (declarative knowledge about procedures) differs from being able to execute them fluently under exam conditions (proceduralised competency). The gap between procedural explanation and sufficient practice opportunities created pedagogical misalignment with assessment demands.

During the critical incident focus group activity, Group B annotated this limitation explicitly:

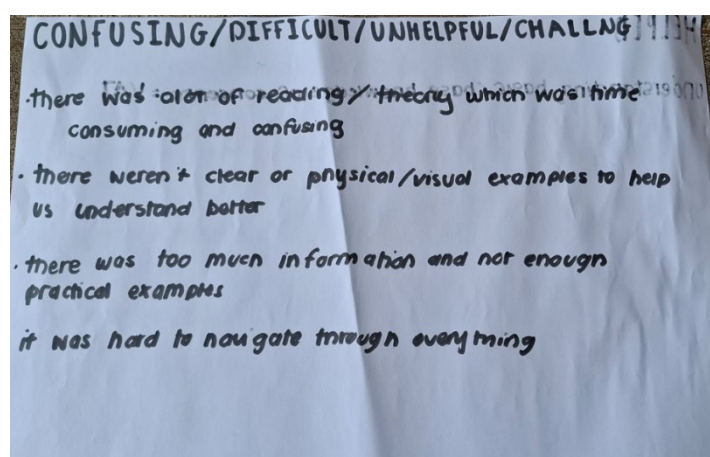


Figure 25: Focus Group Activity _ (Group B)

Written comments on the artefact in Figure 25, above, illustrate students' need for more *“clear, physical/visual practical examples”*.

Students provided suggestions to overcome this limitation. *“If you took the theory and broke it into questions that you will experience in an assessment, that would have been a lot more beneficial to help you figure out the errors and stuff”* (Participant #1). *“I think if it could have an actual example of a proper question, that would be in the exam, not just the theory, but also practical questions that require you to apply the theoretical concepts, that will be helpful”* (Participant #6). Moreover, implicit in Participant #1's commentary is the need for practice questions to gradually become more complex *“Those homework questions were very much like question one, where they'd ask you, like, define a phrase. Or is this true or false? Or like match the columns*

sort of thing, but in terms of like the other questions like question 2 or Question 3, where its more application, the questions were not helpful”.

The three key areas of improvement including the need for more examples with different scenarios, questions that gradually increase in complexity and support students to recognise common mistakes reveal students' metacognitive awareness of their learning needs. The students' commentary illustrates that students understood that expertise development requires varied practice, progressive complexity, and explicit attention to error patterns (Ericsson & Pool, 2016). From an SDL perspective, this represents sophisticated self-monitoring, students accurately assessed that procedural explanations alone were insufficient for developing competency.

5.4.3 Theoretical Interpretation: Declarative Knowledge Foundation Without Procedural Mastery

Findings in this section reveals that AI resources effectively supported declarative knowledge acquisition, helping students learn what Accounting concepts mean and what procedures involve, but contributed minimally to procedural knowledge mastery, the fluent execution of Accounting techniques under varied conditions.

This pattern aligns with cognitive learning theory's distinction between knowledge types according to Anderson (1983). Declarative knowledge is described as factual information, concepts, principles (e.g., "Assets equal liabilities plus equity"). Procedural knowledge affords explicit insights into how to perform tasks and procedures (e.g., actually preparing journal entries and ledger accounts). Conditional knowledge refers to when and why specific procedures should be applied (e.g., recognising when to make adjusting entries).

AI resources primarily addressed declarative knowledge, with limited procedural support and virtually no conditional knowledge development. This is pedagogically problematic in professional education contexts like Accounting, where procedural and conditional knowledge are essential for competent practice (Alexander et al., 1991).

From an SDL perspective, this limitation constrained self-monitoring capabilities. Students could use AI to check conceptual understanding ("Do I know what VAT is?") but could not effectively assess procedural competency ("Can I complete all VAT calculations?"). Without adequate practice opportunities integrated into AI resources,

students had to seek procedural development elsewhere, reducing AI's PU for comprehensive learning support.

TAM explains why this limitation mattered, in that PU depends on the technology's capacity to improve performance on tasks users value (Davis, 1989). Students valued exam success, which required procedural competency. When AI did not adequately support procedural development, PU remained moderate despite effective declarative knowledge support.

5.5 How AI Shaped Skill Development: Lower-Order Support, Higher-Order Neglect

This section addresses the second component of Research Question 2: How did the customised Generative AI tool shape students' skill development in ACC1A? Findings reveal an asymmetric pattern whereby AI resources effectively supported lower-order cognitive skills (remembering, understanding, and basic application) as defined by Bloom's revised taxonomy (Anderson & Krathwohl, 2001), but provided minimal support for higher-order skills (analysis, evaluation, and creation). This pattern explains Chapter 4's finding that students had mixed perceptions of learning reinforcement and confidence building.

5.5.1 Supporting Lower-Order Cognitive Skills: Remembering and Understanding

AI-generated pathway questions effectively supported remembering and understanding, the two foundational levels of Bloom's taxonomy. Questions typically required students to recall definitions, recognise Accounting terminology, or demonstrate basic comprehension of concepts.

Participant #8 described using pathway questions for memorisation, "*The questions helped me remember terminology. When it asked, 'What is the Accounting equation?' or 'Define a current asset,' I had to recall the definitions from the summaries. That repetition helped me memorise the basics.*"

This represents Bloom's "remembering" level, retrieving relevant knowledge from long-term memory. While sometimes dismissed as superficial, memorisation of foundational concepts and terminology is essential in disciplines like Accounting where technical vocabulary mediates professional communication and reasoning (Alexander et al., 1991). AI-generated questions provided low-stakes opportunities to practice

retrieval, which strengthens memory consolidation through the testing effect (Roediger & Karpicke, 2006).

Participant #14 described comprehension-level support, *"Some questions asked me to explain the difference between income and expenses, or to give examples of each. That made me think about what each concept means, not just memorise definitions. I had to understand the concepts to answer."*

This represents Bloom's "understanding" level or constructing meaning from information through interpreting, exemplifying, classifying, summarising, or explaining. Understanding-level questions required more than rote recall; students needed to grasp conceptual relationships and generate examples, indicating genuine comprehension rather than surface memorisation.

From an SDL perspective, pathway questions supported self-monitoring at foundational knowledge levels. Students could assess whether they had memorised core terminology and understood basic concepts, identifying knowledge gaps requiring additional study. Participant #3 explicitly described this self-assessment function, *"If I got questions wrong about basic concepts, I knew I needed to go back and reread that section. The questions showed me what I didn't understand yet."*

This represents effective use of formative assessment for self-diagnosis, a critical SDL competency (Garrison, 1997). However, this self-monitoring capacity was limited to lower-order knowledge; students lacked tools for assessing higher-order skill development.

5.5.2 Limited Support for Application: Surface-Level Practice

Some pathway questions addressed Bloom's "application" level, requiring students to use procedures in familiar contexts. However, qualitative data revealed that application opportunities were limited in scope and complexity.

Participant #13 described application-level questions, *"There were some questions that asked you to prepare a simple journal entry or classify accounts. So, you had to apply what you learned, not just remember it. But the questions were basic, much simpler than textbook exercises or exam questions."*

The key phrase "basic, much simpler than" indicates that while questions nominally assessed application, they did not require the depth or complexity of application demanded in assessments. This represents pseudo-application whereby students followed familiar procedures in highly scaffolded contexts without encountering the problem-solving challenges characteristic of genuine application in novel situations.

Group D's focus group discussion elaborated this limitation:

Group D, Student 1, *"The practice questions felt like they were just testing if you understood the concept, not if you could actually do Accounting. Real Accounting problems are more complicated."*

Group D, Student 2, *"Yes, in exams we get scenarios where you have to figure out what to do, read information and extract what matters, make decisions. The AI questions just give you everything clearly, no thinking required."*

This distinction between simplified, scaffolded practice and complex, authentic application is pedagogically significant. Authentic application requires problem representation, deciding which procedures apply, managing cognitive complexity, and monitoring solution accuracy (Chi & VanLehn, 2012). AI questions, by providing excessive scaffolding and reducing complexity, did not prepare students for the cognitive demands of assessment tasks.

From a constructive alignment perspective (Biggs & Tang, 2011), this represents misalignment between learning activities (simplified AI questions) and assessment tasks (complex exam problems). Students recognised this misalignment and rationally sought alternative resources (past papers, textbook exercises) that better matched assessment demands. This pedagogical gap significantly undermined PU, explaining neutral or negative perceptions among students seeking comprehensive exam preparation.

5.5.3 Neglect of Higher-Order Skills: Analysis, Evaluation, and Creation

Pathway questions provided virtually no support for higher-order cognitive skills such as analysis (breaking concepts into components and determining relationships), evaluation (making judgments based on criteria), or creation (putting elements together to form a coherent whole). This limitation was extensively critiqued by students.

Participant #13 identified the absence of analytical challenges, *"The questions don't ask you to analyse anything. They don't ask 'Why would this transaction affect this account?' or 'What's the difference between these two Accounting treatments?' Those deeper questions would help you really understand, but the AI doesn't ask them."*

Analysis-level questions require students to examine relationships, distinguish between alternatives, and explain reasoning. These cognitive activities promote deeper understanding and prepare students for professional practice where accountants must analyse complex situations and justify treatments (Alexander et al., 1991). The absence of analytical questions meant AI resources supported content coverage but not critical thinking development.

Participant #4 noted the lack of evaluative tasks, *"In Accounting, you need to make judgments sometimes. Like which depreciation method is more appropriate for this asset? Or does this transaction require an adjusting entry? The AI questions never asked these kinds of evaluative questions where you have to weigh options and decide."*

Evaluation-level tasks require students to apply criteria, make decisions, detect inconsistencies, or judge appropriateness. These skills are essential for professional accountants who must exercise professional judgment (Sangster, 2022). The exclusively lower-order focus of AI questions left students unprepared for judgment-based tasks in assessments and professional practice.

Creation-level skills (designing solutions, producing original work, combining elements in novel ways) were entirely absent from AI resources. Given that creation represents the highest cognitive level and is challenging to assess even in traditional pedagogy, its absence from AI-generated questions is perhaps unsurprising. However, this means AI contributed nothing to students' development of synthetic, creative problem-solving capacities.

Group C's written artefact from the focus group activity included this annotation on an AI-generated summary depicted in Figure 26:

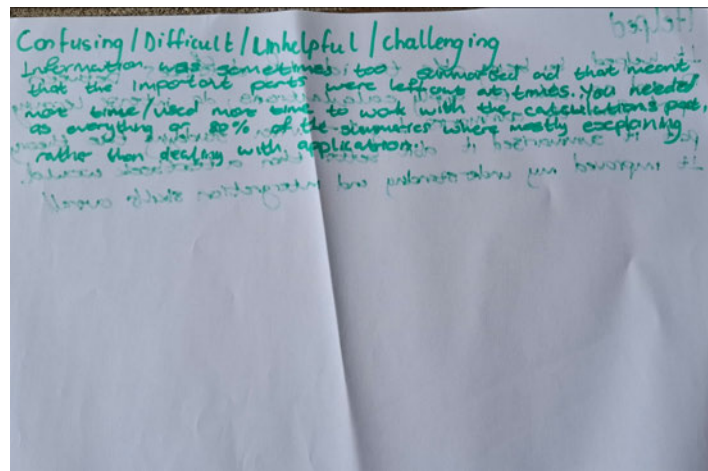


Figure 26: Figure 7: Focus Group Activity _ (Group C)

The reference to *“mostly explaining”* translates into the *“what;”* indicative that the summaries explained what to do but not why, *“dealing with application”*. Understanding why helps you apply knowledge in new situations. This suggests that students needed summaries or questions that supported their understanding of the *“why”*, not just *“what”*.

This comment reveals the sophisticated metacognitive awareness that students possessed, which expressed that students understood that higher-order understanding (conditional knowledge, ie. knowing why procedures apply in certain contexts) enables transfer to novel situations, while lower-order knowledge (declarative, ie. knowing what procedures exist) supports only routine application in familiar contexts. Their recognition that AI resources neglected *“why”* questions demonstrates pedagogical insight often attributed to lecturers rather than students.

5.5.4 Implications for Self-Directed Learning Development

SDL theory posits that effective learning environments promote self-management, self-monitoring, and intrinsic motivation (Garrison, 1997). AI resources' focus on lower-order skills had mixed implications for SDL development.

Positive SDL support entailed self-management, whereby in-demand access enabled students to independently practice foundational knowledge. Secondly, self-monitoring at basic levels, in that students could assess whether they had memorised terminology and understood concepts. Thirdly, structured guidance, presented as clear explanations and procedural steps provided scaffolding for autonomous learning

SDL limitations included limited self-monitoring at higher levels as students lacked tools for assessing analytical or evaluative competencies. Secondly, insufficient challenge due to lower-order focus which did not push students toward deeper cognitive engagement. Thirdly, reduced intrinsic motivation expressed through students' recognition that AI questions didn't match exam demands, instrumental motivation (passing exams) could not be satisfied, and intrinsic motivation (understanding for its own sake) was not stimulated by cognitively demanding tasks

Participant #10 captured this SDL tension, *"I liked having control over when and how much I used the AI, that felt self-directed. But the content itself didn't challenge me to think deeply or become more independent in my learning. It supported surface learning, which is useful, but I needed more to really develop as an Accounting student."*

This insight reveals a crucial distinction pertaining to technological affordances for learner autonomy (self-paced, on-demand access) do not automatically translate to cognitive autonomy or deep learning. SDL requires not just control over learning logistics but also engagement with cognitively demanding tasks that promote genuine understanding and independent thinking (Garrison, 1997). AI resources provided logistical autonomy but insufficient cognitive challenge.

5.5.5 Theoretical Synthesis: Skill Development Profile

Synthesising findings from this section, AI resources generated an asymmetric skill development profile (presented in Figure 27):

Cognitive Skill Level (Bloom's Taxonomy)	AI Support Level	Evidence
Remembering	Strong	Pathway questions effectively tested recall of definitions, terminology, principles
Understanding	Moderate - Strong	Questions required explanation, exemplification, and conceptual comprehension
Application	Weak	Limited practice with simplified problems insufficient for developing procedural fluency
Analysis	Absent	No questions requiring examination of relationships, comparisons, or justification of reasoning

Evaluation	Absent	No questions requiring judgment, critique, or selection among alternatives
Creation	Absent	No questions requiring synthesis, design, or production of original solutions

Figure 27: Synthesised findings indicating that AI resources generated asymmetric skill development

This profile reveals a pedagogical limitation, illustrating that AI resources supported knowledge acquisition (lower-order) but not knowledge application in complex, authentic contexts (higher-order). In professional education like Accounting, where graduates must perform complex problem-solving in variable workplace contexts, higher-order skill development is essential (Alexander et al., 1991).

From a TAM perspective, this limitation explains moderate PU. Students valued AI for foundational learning but recognised its insufficiency for comprehensive competency development, producing neutral overall perceptions. From an SDL perspective, the lower-order focus provided initial scaffolding but did not support progression toward autonomous, expert-level performance requiring analytical and evaluative capacities.

5.6 Why Students Perceived Benefits: Conditions for Effective AI Use

This section addresses the first component of Research Question 3: Why did first-year students perceive AI-generated resources as beneficial in supporting their learning? Qualitative findings reveal that benefits were conditional, depending on students' learning stage, their specific learning needs, and how strategically they integrated AI into broader study practices. This section explains Chapter 4's finding that 48-58% of students perceived benefits across various dimensions while 40-47% remained neutral.

5.6.1 Benefits for Initial Topic Introduction and Conceptual Overview

Students most consistently perceived benefits when using AI resources for initial topic introduction at the beginning of new Accounting chapters. The summaries provided accessible entry points into unfamiliar content, reducing cognitive overwhelm and building confidence before engaging with more detailed materials.

Participant #2 described this strategic use, *"At the start of each new topic, I'd read the AI summary first before going to the textbook or lecture slides. It gave me a basic understanding of what the topic was about, the main concepts, the key terminology."*

Then when I went to the textbook, I wasn't completely lost because I had that foundation."

This represents effective use of AI as an advance organiser (Ausubel, 1968), providing cognitive structure that facilitates integration of subsequent, more detailed information. From an SDL perspective, this demonstrates self-management, students proactively sought accessible introductions to new content, controlling the pace and sequence of their initial learning. The on-demand availability of AI summaries supported autonomous learning flows without requiring instructor intervention.

Responses from some of the participants revealed this benefit was particularly pronounced for students who struggled with lectures:

"When I was doing a VAT, I didn't really understand it well when the lecturer was teaching us, and then when I did use the summaries, it gave me more understanding on how to do this concept," Participant #12.

"You know in class when the lecturer would explain, you'd still be confused here and there and then maybe there's no time to ask questions and if you text them on the side, they're still a bit busy. They're doing their own thing. This is where the AI was helpful. I would go back and re-listen to the lecture recording and it made more sense," Participant #11.

This finding highlights an equity consideration illustrating that AI resources may particularly benefit students who struggle to keep pace with live instruction due to prior knowledge gaps, language barriers, or processing speed differences. By providing alternative explanations in clear, structured formats, AI can reduce disadvantage for students who don't thrive in fast-paced lecture environments. However, this benefit depends on accessibility; students lacking reliable internet or appropriate devices may not access these compensatory resources, potentially exacerbating rather than reducing inequality.

From a TAM perspective, students perceived AI as useful specifically for the task of initial topic familiarisation. Usefulness perceptions depend on task-technology fit (Goodhue & Thompson, 1995), meaning when AI capabilities aligned with students' needs (accessible introduction to unfamiliar content), PU was high. When capabilities

did not align with needs (exam preparation requiring complex problem-solving), PU declined.

5.6.2 Benefits for Self-Paced Review and Retrieval Practice

Students valued the ability to revisit AI-generated summaries and questions for self-paced review and retrieval practice, particularly when preparing for assessments. The on-demand nature of AI resources supported personalised study schedules and individual learning rhythms.

Participant #11 described using AI for pre-exam review: *"Before the test, I went through all the AI summaries again to refresh my memory on key concepts. It was quicker than re-reading the whole textbook, and it highlighted the most important points. Then I tested myself with the pathway questions to see what I remembered."*

This represents strategic use of AI for spaced retrieval practice, a learning technique proven to enhance long-term retention (Roediger & Karpicke, 2006). By revisiting content at intervals and testing retrieval through questions, students strengthened memory consolidation. The efficiency of accessing condensed summaries rather than extensive textbook chapters reduced time costs, making review more feasible within constrained study schedules.

From an SDL perspective, this self-paced review capability supported both self-management (students controlled timing and frequency of review) and self-monitoring (pathway questions enabled assessment of retention). Participant #4 explicitly described the self-monitoring function, *"When I did the pathway questions and got some wrong, I knew which topics I needed to review more. It helped me identify weak areas rather than just reading everything again."*

This diagnostic use of formative assessment is a core SDL competency (Garrison, 1997) requiring self-directed learners to accurately assess their knowledge state to allocate study effort effectively. AI questions, despite their limitations for higher-order skill development, effectively supported self-monitoring at foundational knowledge levels.

However, qualitative data also revealed that the benefit of retrieval practice was limited by question simplicity in that the pathway questions helped students to remember concepts, but didn't prepare them for exam-level questions requiring critical thinking

and problem solving; *"It helped to remember as I said before, recall information, but not really critical thinking or problem solving," Participant #3.*

5.6.3 Benefits for Building Initial Confidence in an Unfamiliar Discipline

Several students, particularly those without prior Accounting knowledge, described AI resources as confidence-building tools that reduced anxiety about engaging with an unfamiliar, technically demanding discipline.

Participant #11 explained how AI reduced intimidation, *"for someone that has never done Accounting and also you don't have full confidence of whatever you will be writing, especially for your first Test, I mean, you're very scared, so it's already prepared me for the questions and how to answer the questions. That was one of the best things that helped me a lot."* Similarly, Participant #5 commented on the motivational aspect of the tool *"when you get the question right and the confetti comes up on the screen. It made me feel like I know my work and I'm going to do great in my test."*

This affective benefit, reduced anxiety and increased self-efficacy, is pedagogically significant. Self-efficacy (belief in one's capability to succeed) influences effort expenditure, persistence, and ultimately achievement (Bandura, 1997). When students develop initial confidence through accessible resources, they are more likely to engage persistently with challenging content. From an SDL perspective, self-efficacy is foundational to intrinsic motivation: students who believe they can succeed are more likely to pursue learning for its inherent value rather than only external rewards (Garrison, 1997).

These comments reveal that AI resources served not just cognitive (knowledge transmission) but also affective (emotional support) functions. For first-year students navigating transitions to university-level study in technical disciplines, affective support can be as important as cognitive support for persistence and success (Tinto, 2017).

However, Participant #1, a high-achieving student with prior Accounting knowledge, did not experience this benefit: *"I didn't need confidence-building because I already knew I could do Accounting. For me, the AI was too basic and didn't challenge me, so I didn't use it much."* This reveals that confidence-building benefits were greatest for

novice learners, while more advanced students found AI less useful, contributing to varied perceptions across the cohort.

5.6.4 Benefits of Multimodal Access and Learning Flexibility

Students appreciated the mobile accessibility of AI resources via the MathU App, which enabled learning in diverse contexts and time slots. This flexibility supported integration of learning into daily routines and enabled opportunistic study moments.

Participant #5 described this flexibility: *"I could access the summaries whenever I had free time, because I could access the App on my phone to see if I know what I am doing. Like if I had a break between classes or was waiting for transport, I could quickly review a topic on my phone. That flexibility helped me fit more study into my day. Then I reward myself with Tiktok afterwards."*

This represents effective use of mobile learning affordances comprising portability, connectivity, and context-sensitivity (Traxler, 2009). For students with complex schedules involving work, family responsibilities, or long commutes, the ability to study in fragmented time periods rather than requiring extended desk-based sessions increases total learning time and supports persistence.

From an SDL perspective, mobile access enhanced self-management by removing logistical barriers to autonomous learning. Students did not need to wait for access to computers or physical libraries; learning resources travelled with them. This aligns with SDL theory's emphasis on learner control over learning conditions (Knowles, 1975).

However, as discussed in Section 5.3.2 and elaborated in Section 5.7.2, mobile-only access also created challenges. Some students found phone-based study distracting or inadequate for deep learning, revealing that the same technological affordance (mobile access) generated both benefits and challenges depending on individual preferences and study contexts.

5.6.5 Theoretical Interpretation: Conditional Usefulness and Individual Variation

Synthesising findings from this section, AI benefits were consistently conditional, depending on four factors. Firstly, the learning stage, as AI was most useful for initial topic introduction and conceptual review, less useful for advanced application and exam preparation. Secondly, learner characteristics as AI particularly benefited novice

learners requiring confidence-building and foundational concept introduction, less beneficial for advanced learners seeking cognitive challenge. Thirdly, learning context as AI suited fragmented study time and mobile learning contexts, less suitable for extended, focused study requiring deep processing. Lastly integration strategy based on the finding that AI was useful when strategically integrated with other resources (textbooks, lectures, past papers) as one component of a comprehensive study approach, less useful if relied upon exclusively

This pattern illuminates Chapter 4's finding that perceptions divided roughly into thirds (agree/neutral/disagree). Students who used AI strategically for purposes it supported well (initial learning, conceptual review) within broader study ecosystems perceived clear benefits. Students who expected AI to comprehensively support all learning needs, particularly exam preparation requiring higher-order skills, experienced disappointment. Students whose learning preferences or contexts did not align with AI affordances (e.g., preferring extended desk-based study rather than mobile learning) found limited value.

From a TAM perspective, this conditional usefulness pattern reveals the importance of task-technology fit. PU depends not just on technology quality but on alignment between technology capabilities and user needs (Goodhue & Thompson, 1995). AI resources had genuine strengths (accessible concept explanation, on-demand retrieval practice, mobile accessibility) but also clear limitations (insufficient application practice, lower-order focus, mobile-only access). Students who needed strengths of the AI resources perceived benefits; students who needed capabilities AI lacked perceived limited usefulness.

From an SDL perspective, conditional benefits raise questions about whether AI resources adequately supported progression toward autonomous, self-directed learning. While AI provided initial scaffolding and supported self-monitoring at basic knowledge levels, the neglect of higher-order skills meant students remained dependent on other resources (instructors, textbooks, peers) for developing advanced competencies. Effective SDL support should enable gradual withdrawal of scaffolding as learners develop expertise (Garrison, 1997), but AI resources provided consistent foundational support without pathways to advanced autonomous practice.

5.7 Why Students Perceived Challenges: Barriers to Effective AI Use

This section addresses the second component of Research Question 3: Why did first-year students perceive AI-generated resources as challenging or problematic in supporting their learning? Findings reveal four interconnected challenge categories, pedagogical misalignment, usability barriers, insufficient accommodation of learning diversity, and limitations in AI responsiveness. These challenges explain Chapter 4's finding that 40-47% of students provided neutral responses and that EOU strongly predicted PU.

5.7.1 Pedagogical Misalignment: The Theory-Practice Gap

The most substantive and frequently articulated challenge was the pedagogical misalignment between AI-generated content and ACC1A module requirements. Students consistently reported that AI resources focused excessively on theoretical, declarative knowledge while the module demanded practical, procedural competency, particularly in assessments.

Participant #13 articulated this misalignment comprehensively, *"So with the App actually simplifying the notes, the questions themselves end up being a bit too simple because it's not the same level as what we get asked in the assessments. I guess like it's useful and it helps, you know, these things, but it's not challenging or enough to be worthwhile. If I'm gonna be honest. I think it would help at like the grassroots level because it does give very basic, very simple explanations, which is awesome when you're still trying to grasp the concepts. But once you're comfortable and you need to know the more challenging aspects of it, it's not going to be of much help."*

This commentary captures the pedagogical problem; procedural skills require embodied practice, not just conceptual knowledge (Ryle, 1949). Professional competencies in disciplines like Accounting develop through repeated execution of procedures in varied contexts, allowing proceduralisation (transformation of declarative knowledge into automatic skills) to occur (Anderson, 1983). AI resources provided conceptual foundations but insufficient practice opportunities for proceduralisation.

Group C's focus group discussion elaborated specific manifestations of theory-practice imbalance:

Group C, Student 1: *"With the words alone it not enough. I wish it could have explained other more complicated things like what you do when bank account is negative/how do you record it because that is what we as students are being tested on."*

Group C, Student 2: *"It is very vague and does not go into alot of detail, which I need to understand better. The structure and the layout is good and simple to follow which helps me understand but the information included is too vague and there needs to be more examples to practice to understand better."*

These comments further reveal assessment misalignment. AI content did not match the format, complexity, or cognitive demands of actual assessment tasks. From a constructive alignment perspective (Biggs & Tang, 2011), this misalignment is pedagogically problematic. Constructive alignment theory proposes that learning outcomes, teaching/learning activities, and assessment tasks should align to create coherent learning experiences. When students practice lower-order knowledge (definitions, true/false questions) but are assessed on higher-order application (complex problem-solving), a gap emerges that undermines learning effectiveness and student confidence.

This pedagogical misalignment directly explains Chapter 4's finding that 58% valued AI primarily for exam preparation despite only 48% finding it useful for exam preparation. Students wanted exam preparation support, but AI resources failed to provide it adequately. This created a PU deficit that contributed significantly to neutral or negative overall perceptions.

Participant #6's comment captures the consequence: *"I don't think it's necessarily helpful for Accounting because it's such an application subject. But I think if it was something like Constitutional law, that's basically just theory that you have to study, I think it would be more helpful for something like that. I think if it could have an actual example of a proper question that would be in the exam, not just the theory, but also practical questions that require you to apply the theoretical concepts. For me personally, I know they're not going to ask multiple choice questions, especially because Accounting is more, like you have to actually do it, so I didn't see the point in using the AI tool anymore and stopped using it."* As a result, students used alternate resources *"I think the summaries help in terms of helping me with my theory, but other*

than that I'd say my other progress in my module was purely helped from my lecturer and my textbooks and practicing over and over again" Participant #1.

This strategic abandonment of AI for high-stakes preparation reveals rational student behaviour, that is when resources don't align with assessment demands, students reallocate effort to more relevant materials. From an SDL perspective, this demonstrates appropriate self-management (prioritising effective study methods), but from a pedagogical effectiveness perspective, it indicates AI resources failed to adequately support comprehensive learning.

The theory-practice imbalance also limited scaffolding. Effective scaffolding gradually increases complexity and withdraws support as learners develop expertise (Wood, Bruner, & Ross, 1976). AI resources provided consistent foundational support but did not scaffold progression to intermediate and advanced complexity levels.

Participant #13 identified this limitation, *"I don't need something explaining basic concepts to me at this point in the semester. I need progressively harder questions that build from simple to complex. Like start with a basic transaction, then add complications, then combine multiple transactions, then introduce scenarios requiring judgment. The AI stayed at the basic level throughout, which stopped being useful after the first few weeks."*

This absence of adaptive difficulty meant AI resources could not support learners across their developmental trajectory. Early in the semester, basic explanations were valuable; later, students needed advanced challenges. The static nature of AI content created a declining usefulness pattern over time, potentially explaining why neutral responses predominated in the questionnaire conducted after eight weeks of usage.

From a Vygotskian perspective, effective instruction operates within learners' Zone of Proximal Development (ZPD), the gap between current independent performance and potential performance with guidance (Vygotsky, 1978). AI resources operated below most students' ZPD after initial topic introduction, providing support they no longer needed rather than challenge at the edge of their current capability. This pedagogical mismatch between learner readiness and resource difficulty undermined both engagement and development.

5.7.2 Usability Barriers: Device Limitations and Interface Challenges

The second major challenge category involved usability barriers stemming from mobile-only access, interface design limitations, and restricted functionality. These barriers directly explain Chapter 4's finding that ease of use strongly predicted PU ($\rho = 0.692$, $p < 0.01$), that is, when usability was poor, students disengaged despite potential content value.

Device Limitations: The Distraction Problem

Multiple students identified mobile phone access as simultaneously beneficial (flexibility, portability) and problematic (distraction, inadequacy for focused study). Participant #13 described the distraction challenge: *"Because it's just on my phone when I'm studying, I don't want to be on my phone because I end up doing other things. I'm not having my phone out while I'm studying. It's not productive for me personally."*

This distraction problem reflects inherent tensions in mobile learning. Phones provide ubiquitous access but also ubiquitous distraction (Giunchiglia et al., 2018). For students lacking strong self-regulation skills, the same device providing learning resources also provides entertainment, social connection, and cognitive escape, creating attention competition. From an SDL perspective, effective self-management requires the ability to resist distractions and maintain focus on learning goals (Garrison, 1997). When the learning tool itself introduces distraction risks, students with weaker self-regulation may struggle to use it effectively.

Participant #4 contrasted mobile access unfavourably with laptop-based study *"On my laptop, I can have the AI summary open in one window, my notes in another. I can copy and paste important points into my notes. On my phone, I can only see one thing at a time, I can't copy text from the AI, I can't easily switch between resources. It's limiting."*

This highlights functional limitations of mobile interfaces which include restricted screen space, limited multitasking capability, and constrained text manipulation. While mobile learning suits brief, fragmented study episodes, it may be inadequate for extended, cognitively demanding learning requiring integration of multiple information sources (Giunchiglia et al., 2018). The inability to copy AI-generated text was

particularly frustrating for students who wanted to compile personalised study notes integrating AI content with other materials.

From a TAM perspective, these device limitations reduced PEOU, which in turn undermined PU. Even valuable content becomes less useful when access is effortful, distracting, or incompatible with preferred study workflows (Davis, 1989).

Interface Design and Navigation Challenges

Several students criticised the AI tool's interface as "unfinished," "clunky," or "frustrating" compared to competing AI applications. Participant #4 provided detailed comparison to TurboLearn, a commercially available AI study tool:

"TurboLearn has everything, quizzes that it generates for you. Then it also generates some notes, you can ask it questions in real time and get the proper explanations for it, and more importantly, you can copy it so that you can read it later. I mean, TurboLearn won by a landslide if there was like a competition, it wouldn't even be a competition, but, for MathU, it still felt unfinished, TurboLearn felt polished and elegant, and slick. You could focus on one topic at a time where you could upload your slides or whatever, and then it created the notes for you, where you uploaded your slides and then it saved that. With MathU, if you wanted to create some other notes based off of other slides, you had to delete the other one. Or if you didn't want to delete the other one then you have to pay premium and then now it's a problem."

This comparison reveals that students benchmarked the institutionally provided AI tool against consumer-grade AI applications optimised for user experience. When institutional tools failed to meet commercial standards, students perceived them as inferior, reducing adoption. From a TAM perspective, this illustrates the competitive context of technology acceptance where PEOU and usefulness are relative, evaluated against alternative technologies users have experienced (Venkatesh & Davis, 2000).

The navigation challenge of finding previous summary content within the App is particularly significant. Unlike web-based platforms with search functionality, organised content libraries, and persistent access, App-based delivery buried content in chronological message streams. Participant #11 described this challenge *"Sometimes I wanted to go back to a summary from two weeks ago, but I had to scroll*

through all the App content to find it. Eventually I just stopped looking for old content because it was too much effort."

This illustrates how poor information architecture (content organisation and retrieval systems) creates usage friction that discourages engagement. From an SDL perspective, effective self-management requires efficient access to learning resources; when retrieval costs are high, students rationally abandon resources in favour of more accessible alternatives (Garrison, 1997).

Inadequate Cross-Platform Availability

Students requested multi-platform access, particularly laptop or web-based interfaces, to accommodate diverse study contexts and preferences. Participant #13 advocated for platform flexibility *"Not everyone wants to study on their phone. Some of us prefer laptops. If there was a web version or app for laptops, I'd use it more because I do most of my serious studying at my desk, not on my phone."*

This request reflects recognition that different learning activities suit different devices. Mobile phones support brief review, quick retrieval, and opportunistic learning in varied locations. Laptops and desktops support extended engagement, note-taking, multitasking, and integration with other digital tools. By restricting access to mobile-only, the AI tool excluded students who preferred or needed laptop-based study, reducing overall adoption and PU.

From a Universal Design for Learning (UDL) perspective (CAST, 2018), providing multiple means of access and engagement is essential for equity. Students have diverse device preferences, technological constraints (some may lack smartphones or data plans), and accessibility needs (larger screens for visual impairment, keyboard access for motor impairments). Mobile-only access created barriers for students whose contexts or needs required alternative platforms.

5.7.3 Insufficient Accommodation of Learning Diversity: Visual, Auditory, and Interactive Needs

The third challenge category involved AI resources' failure to accommodate diverse learning preferences, styles, and accessibility needs. Content was text-heavy, lacking visual representations, audio alternatives, and interactive features that could enhance engagement and comprehension for varied learners.

Visual Learner Needs Unmet

Multiple students identified themselves as visual learners requiring diagrams, charts, tables, and graphical representations to understand concepts. Current AI resources provided exclusively text-based explanations, creating comprehension barriers for visual processors.

Group C's focus group activity artefact (Figure 28) included numerous written comments requesting visual content:

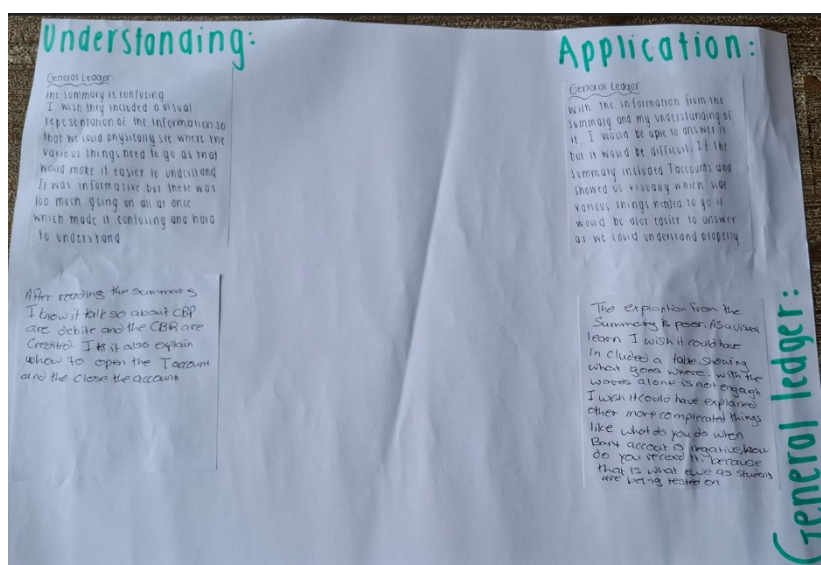


Figure 28: Group C's focus group annotations

- *"If the summary included T-accounts and showed us visually which side various things needed to go, it would be a lot easier to answer as we could understand properly."*
- *"As a visual learner I wish it could have included a table showing what goes where"*

These requests reflect cognitive science findings that visual and verbal information processing involve different cognitive systems, and that presenting information in both formats enhances learning through dual coding (Paivio, 1990; Mayer, 2021). For Accounting concepts involving spatial relationships (e.g., debit/credit positioning in T-accounts, financial statement structure), visual representations can clarify relationships that text alone obscures.

Participant #5's experience as a dyslexic learner illustrated how text-heavy resources created accessibility barriers: *"Because I'm dyslexic, I wish perhaps there was like a*

generative voice that I could use while reading. If summaries could be in diagrams and have specific colours, or even like storytelling. So yeah, so I can understand."

This account reveals how learning differences that don't preclude academic success (dyslexia) can nonetheless create significant barriers when resources are designed without accessibility considerations. From a UDL perspective (CAST, 2018), effective learning resources provide multiple representations (text, visual, audio) to reduce barriers and support diverse learners. AI resources' exclusive reliance on text created inequitable access for students who process information more effectively through alternative modalities.

Auditory Learning and Multimedia Integration

Several students advocated for audio features, including text-to-speech playback and video explanations, to complement text-based summaries.

Participant #8 requested multimedia alternatives: *"I think what might help is if there's some videos or some voice recordings. That would be more beneficial for us to learn than actually seeing the actual writing."*

Participant #13 explained generational preferences for audiovisual content: *"Our generation doesn't like to read, rather hear or watch videos. Before tests and exams, I watch videos to get a better understanding of something. I'm not gonna go read something new. I'm gonna go either watch or listen to something."*

While this generational characterisation may be somewhat stereotypical, it reflects genuine preferences shaped by contemporary media consumption patterns. Students accustomed to YouTube tutorials, educational podcasts, and video-based social media content may find text-only resources less engaging and memorable. From a TAM perspective, when resource formats misalign with user preferences and habits, PEOU declines (Davis, 1989).

Multimedia formats also support cognitive processing in distinct ways. Mayer's (2021) Cognitive Theory of Multimedia Learning demonstrates that combining verbal explanations with visual animations enhances learning by enabling dual-channel processing and reducing cognitive load. Audio narration allows students to process explanations while viewing diagrams simultaneously, whereas text requires sequential processing of written words and visual elements. For complex Accounting procedures

involving multiple steps and spatial arrangements, multimedia presentation could enhance comprehension and retention.

Interactive Features and Engagement Mechanisms

Students compared the AI tool unfavourably to commercial applications offering interactive features like real-time question-answering, personalised quizzes, flashcard generation, and progress tracking. These interactive affordances enhanced engagement and supported diverse learning strategies.

Participant #4 described TurboLearn's interactive features enviously: *"You can ask it questions in real time and get proper explanations. You can generate flashcards for memorisation. It tracks your progress and shows where you've improved. These features make learning more active and engaging."*

The absence of such interactivity in AI resources meant students experienced passive content consumption rather than active knowledge construction. From a constructivist learning perspective, active engagement, learner-directed exploration, and opportunity for questioning and immediate feedback, promote deeper understanding than passive reception of information (Bransford et al., 2000). AI resources provided static content without mechanisms for students to query, explore, or interact, limiting engagement.

Participant #4 even envisioned an AI "study companion" with gamification elements, *"Maybe if some sort of character could be created that actually kept score of your progress. It was like, OK, this is where you started from and this is how far you've come. After you've reached a level, maybe you get notifications from the AI on your phone with daily notes, like a concept about Accounting in your notifications. That would create a bond between the app and the user."*

While this vision may be aspirational, it reflects students' desire for personalised, engaging, relationship-oriented learning experiences. Gamification elements (progress tracking, achievement recognition, goal-setting) can enhance intrinsic motivation by providing competence feedback and creating emotional investment (Deci & Ryan, 2000). From an SDL perspective, progress visualisation supports self-monitoring (students see development trajectories) and motivation (achievement recognition reinforces persistence) (Garrison, 1997).

However, the absence of interactive features in current AI resources meant these engagement and motivation benefits were unavailable. Students experienced AI as a static content repository rather than an adaptive learning partner, limiting emotional connection and sustained engagement.

5.7.4 Limited AI Responsiveness: Need for Human-in-the-Loop Support

The fourth challenge category involved AI's inability to provide human-quality feedback, recognise nuance in student responses, and adapt to individual learning needs. Students valued AI's accessibility but recognised limitations requiring human instructor involvement.

Automated Grading Limitations

Students reported frustration with pathway question grading that marked correct answers wrong when phrasing differed from expected responses. Participant #14 described this limitation: *"Sometimes I'd answer a question correctly but in my own words, and it would mark it wrong because it wanted the exact phrasing from the summary. That's frustrating because I understood the concept, I just expressed it differently. A human marker would recognise that."*

This illustrates a fundamental limitation of current natural language processing illustrating the tool's difficulty recognising semantic equivalence across varied linguistic expressions. While AI can match keywords or exact phrases, it struggles to assess whether conceptually equivalent responses phrased differently demonstrate understanding. This creates two problems, namely false negatives (correct understanding marked wrong) that frustrate students and damage confidence, and failure to provide formative feedback explaining why responses were deemed incorrect.

From an SDL perspective, effective self-monitoring requires accurate feedback on performance (Garrison, 1997). When AI provides inaccurate feedback (marking correct answers wrong), it undermines students' ability to assess their understanding reliably. Students may doubt their comprehension when they are actually correct, or conversely, may believe they understand when they don't, if AI grading is unreliable.

Group D discussed the need for human oversight of AI grading:

Group D, Student 1, *"AI is good for quick feedback, but a human should check the AI's grading to catch mistakes. Especially for written answers where there are multiple correct ways to explain something."*

Group D, Student 2, *"Or at least let us flag answers we think were marked wrong unfairly, and have a human review them."*

These suggestions reflect recognition that hybrid human-AI systems may be more effective than fully automated systems. The "human-in-the-loop" approach, where AI provides initial feedback, but humans monitor quality and intervene for complex or contested cases, combines AI's scalability with human judgment's nuance (Zanzotto, 2019). From a pedagogical design perspective, this suggests AI should augment rather than replace instructor feedback, particularly for complex, open-ended responses requiring interpretive judgment.

Inability to Explain or Tutor

Students noted that AI resources provided correct answers but limited explanations of why answers were correct or how to approach problems. This restricted AI's tutorial function.

Participant #12 contrasted AI limitations with human tutoring *"When I ask my tutor or lecturer why something is done a certain way, they can explain the reasoning, give me alternative examples, relate it to other concepts. The AI just gives me the answer without much explanation. I learn more from the human explanation."*

This highlights that effective tutoring involves not just answer provision but pedagogical scaffolding comprising explaining reasoning, connecting concepts, diagnosing misconceptions, and adapting explanations to learner responses (Chi & VanLehn, 2012). While advanced AI tutoring systems attempt these functions, the relatively simple AI tool deployed in ACC1A lacked sophisticated tutoring capabilities. From an SDL perspective, this limited support for self-monitoring (students couldn't deeply understand errors) and learning (explanations foster conceptual understanding more than answer provision alone).

Participant #4 noted the absence of real-time question-answering: *"With TurboLearn, you can ask it questions as you're studying and get immediate responses. Our AI didn't*

have that. You could only access the pre-made summaries and questions. If you had a specific question about something confusing, you couldn't just ask it."

The inability to ask follow-up questions or request clarification meant AI resources functioned as static content libraries rather than responsive learning partners. Conversational AI interfaces enabling natural language question-answering could provide more personalised support, allowing students to pursue individual curiosities and address specific confusions (Zawacki-Richter et al., 2019). However, implementing sophisticated conversational AI requires substantial technological infrastructure and careful pedagogical design, which may have been beyond the pilot implementation's scope.

Non-Adaptive Content Delivery

AI resources delivered identical content to all students regardless of prior knowledge, learning pace, or demonstrated competency. This lack of personalisation meant content was too basic for some students and potentially too advanced for others.

Participant #1, a high-achieving student with prior Accounting knowledge, found content insufficiently challenging, *"The AI explained things I already knew from high school Accounting. I wanted more advanced material, deeper explanations, harder practice questions. But everyone got the same basic content regardless of their level."*

Conversely, students who struggled with foundational concepts might have benefited from additional scaffolding, more examples, or remedial content that higher-achieving students didn't need. Adaptive learning systems can personalise content, pacing, and difficulty based on ongoing assessment of learner performance, potentially enhancing effectiveness for diverse learners (VanLehn, 2011). However, implementing genuine adaptivity requires sophisticated algorithms, extensive content libraries spanning difficulty levels, and continuous assessment data, all of which were absent from this AI implementation.

From an SDL perspective, adaptive personalisation could support self-monitoring by providing individualised feedback on progress and targeting content to learners' zones of proximal development. However, without adaptive capabilities, AI resources functioned as one-size-fits-all content that fit some students reasonably well but others poorly, contributing to varied perceptions.

Human Oversight and Quality Assurance Needs

Students advocated for human instructor oversight of AI-generated content to ensure accuracy, relevance, and pedagogical quality. Group A's discussion included this exchange:

Group A, Student 3, *"Sometimes the AI summaries had information I wasn't sure was correct, or seemed too simplified. I'd check with the textbook or ask my lecturer to verify. We need lecturers to review AI content before giving it to students."*

Group A, Student 1, *"Yes, and lecturers should decide which topics the AI covers. Not all topics needs AI support; some are better taught other ways."*

This reveals appropriate scepticism about AI-generated content and recognition that human expertise remains essential for quality assurance. From a pedagogical design perspective, this suggests AI should be integrated as one tool within instructor-designed learning ecosystems rather than deployed autonomously. The "human-in-the-loop" principle applies not just to grading but to content curation, error detection, and pedagogical alignment verification (Zanzotto, 2019).

5.7.5 Theoretical Interpretation: Challenge Convergence and Implications

The four challenge categories, pedagogical misalignment, usability barriers, insufficient learning diversity accommodation, and limited AI responsiveness, are interconnected and mutually reinforcing. Pedagogical misalignment reduced PU, while usability barriers reduced PEOU; together, these TAM constructs determined adoption (Davis, 1989). Insufficient accommodation of learning diversity and limited AI responsiveness further undermined both usefulness (content didn't meet diverse needs) and EOU (lack of adaptivity and interactivity increased cognitive effort).

From an SDL perspective, challenges revealed that AI resources supported some SDL dimensions (self-management through on-demand access) while hindering others (self-monitoring limited by inaccurate feedback, motivation undermined by assessment misalignment). Effective SDL environments require not just learner autonomy but also high-quality resources, accurate feedback mechanisms, and support for diverse learning approaches (Garrison, 1997). AI resources provided autonomy without sufficient quality, accuracy, or diversity support.

The convergence of challenges explains Chapter 4's finding that 40-47% of students remained neutral. These students likely experienced both benefits and challenges, recognising AI's value for specific purposes while also encountering substantial limitations. Neutral responses thus represent nuanced, conditional assessments rather than confusion or apathy.

5.8 Limitations of Qualitative Findings

Several methodological and contextual limitations constrain interpretation and transferability of qualitative findings.

5.8.1 Generalisability Constraints

Single-Campus Sampling

All 24 qualitative participants attended Pietermaritzburg campus, representing only 6.7% of Chapter 4's quantitative questionnaire respondents. Findings may not transfer to larger, urban campuses (Sandton, Durban Westville) where students may have different socioeconomic backgrounds, technological access, prior AI exposure, and learning expectations. Regional context, infrastructure quality, and campus culture may significantly shape experiences in ways this study cannot capture.

Small Sample Size

With 14 interview participants and 10 focus group participants, this study may not have achieved full thematic saturation. While major themes became evident, subtler patterns, minority experiences, or campus-specific phenomena may have been missed. Larger qualitative samples spanning multiple campuses would enhance confidence in theme robustness and transferability.

Demographic Imbalances

Female overrepresentation (62.5% versus 40.9% in survey) and potential underrepresentation of certain racial groups limit claims about representative experiences. While no obvious gender or racial patterns emerged in this analysis, more balanced sampling might reveal differences my analysis missed.

5.8.2 Methodological Limitations

Retrospective Self-Report Bias

Interviews and focus groups occurred weeks after AI tool usage concluded. Students reconstructed experiences from memory, potentially emphasising memorable events (particularly frustrations or successes) while forgetting routine interactions. Retrospective accounts may also be rationalised; students may have constructed coherent narratives explaining their AI usage decisions that differ from actual moment-by-moment choices made during the semester.

Concurrent data collection methods (e.g., learning journals, experience sampling, think-aloud protocols during AI use) would provide more accurate accounts of lived experiences but were not feasible within this study's constraints.

Social Desirability and Demand Characteristics

Despite assurances of confidentiality and encouragement of honest criticism, students may have moderated critiques given my role as researcher embedded within Emeritus College. They may have perceived institutional pressure to endorse AI initiatives, or conversely, may have amplified criticisms believing I sought justification for AI improvements. The power dynamic between researcher-educator and student-participants creates unavoidable social desirability pressures requiring acknowledgment.

Focus Group Dynamics

Group discussions may have privileged dominant voices while suppressing divergent perspectives. Students with strong opinions or assertive personalities may have shaped group narratives, while quieter students may have conformed to emerging consensus rather than voicing alternative views. The small group sizes (2-3 participants) somewhat mitigated this risk by reducing pressure to conform, but group dynamics nonetheless influenced data generation in ways individual interviews would not.

5.8.3 Researcher Positionality and Reflexivity

My dual role as Head of Campus at Emeritus College and researcher investigating an institutionally implemented AI tool created potential bias toward favourable interpretations. While I practiced reflexivity, maintained critical distance through deliberate attention to negative evidence, and employed systematic thematic analysis

rather than cherry-picking supporting quotes, my embeddedness in the institutional context may have limited critical perspective.

An external researcher unfamiliar with Emeritus College's context might have asked different questions, noticed different patterns, or interpreted findings differently. Conversely, my insider knowledge enabled rapport-building with participants, contextually informed interpretation, and access that external researchers might struggle to achieve. This insider-outsider tension is inherent in practitioner research and requires acknowledgment rather than resolution (Merriam & Tisdell, 2016).

5.8.4 Temporal and Contextual Specificity

Findings reflect experiences during a specific semester (2025), with a specific AI tool implementation (customised MathU App), in a specific disciplinary context (first-year Accounting). AI technology, pedagogical practices, and student digital literacy are rapidly evolving. Findings may not transfer to different technologies (more advanced AI), different implementations (web-based platforms, integrated learning management systems), or different time periods as both AI capabilities and student expectations develop.

5.8.5 What Questions Remain Unanswered

Despite comprehensive inquiry, several important questions remain unanswered:

Actual Learning Outcomes

This study examined perceived learning benefits but did not measure actual learning outcomes through objective assessments. Do students who used AI extensively perform better in exams than non-users? Does AI support translate to genuine competency development or only perceived understanding? These questions require quasi-experimental or experimental designs comparing AI users and non-users on objective performance measures.

Long-Term Impact

Does AI tool usage in first-year courses influence learning approaches, self-directed learning capacity, or academic performance in subsequent years? Longitudinal studies tracking students across multiple years could assess whether early AI exposure develops self-directed learning skills or creates dependency on technological support.

Differential Effectiveness

Which student characteristics (prior knowledge, learning styles, self-regulation capacity, digital literacy) moderate AI effectiveness? Larger quantitative samples enabling subgroup analyses or qualitative comparative case studies of high-success and low-success AI users could identify factors distinguishing effective from ineffective adoption.

Optimal Design Features

What specific AI features (adaptive difficulty, multimedia formats, sophisticated tutorial capabilities) would address identified limitations? Design-based research iteratively testing enhanced AI versions could generate evidence-based design principles for educational AI in professional disciplines like Accounting.

These unanswered questions represent productive directions for future research extending beyond this exploratory case study's scope.

5.9 Conclusion

This chapter presented qualitative findings addressing how and why customised AI tools shaped first-year Accounting students' learning experiences. Through semi-structured interviews with 14 students and focus group discussions with 10 students, the study revealed that AI resources provided genuine but conditional value, with effectiveness mediated by multiple factors.

Key findings addressing Research Question 2 (How did AI shape learning outcomes and skill development?) include:

1. AI effectively supported foundational declarative knowledge acquisition, providing accessible explanations of Accounting concepts and terminology
2. AI provided limited procedural knowledge development, outlining steps but offering insufficient practice for fluency
3. AI supported lower-order cognitive skills (remembering, understanding, basic application) while neglecting higher-order skills (analysis, evaluation, creation)
4. The theory-practice imbalance meant students developed conceptual understanding but inadequate practical competency for assessment success

Key findings addressing Research Question 3 (Why did students perceive benefits or challenges?) include:

Benefits occurred when:

- AI was used for initial topic introduction and conceptual overview (advance organiser function)
- Students strategically integrated AI with other resources rather than relying exclusively
- Novice learners needed confidence-building through accessible explanations
- Students valued flexible, mobile access for fragmented study time

Challenges occurred when:

- Pedagogical misalignment between AI content (theory-focused) and assessment demands (practice-focused) created usefulness deficits
- Usability barriers (mobile-only access, poor interface, limited functionality) prevented sustained engagement
- Insufficient accommodation of learning diversity (visual/auditory needs unmet, lack of interactivity) alienated certain learner types
- Limited AI responsiveness (inaccurate grading, inability to explain reasoning, non-adaptive content) required human-in-the-loop support

Theoretical implications span both Self-Directed Learning and Technology Acceptance Model frameworks:

From an SDL perspective, AI resources supported some dimensions of self-directed learning (self-management through on-demand access, self-monitoring at foundational knowledge levels) while limiting others (higher-order self-monitoring, intrinsic motivation through cognitive challenge, progression toward expert autonomy). This partial SDL support suggests AI functioned as initial scaffolding but could not support the full developmental trajectory from novice to self-directed expert learner.

From a TAM perspective, the strong relationship between EOU and PU observed quantitatively (Chapter 4) was explained mechanistically through qualitative findings; usability barriers prevented engagement, engagement was necessary for benefit

realisation, therefore usability determined usefulness. This demonstrates that pedagogically sound content cannot generate learning value if poor user experience prevents access.

Integration with Chapter 4 quantitative findings revealed that numerical patterns (neutral responses, ease of use-usefulness correlations, instrumental orientations) reflected complex, conditional realities. Students who responded "neutral" were not confused; they accurately assessed that AI helped in some contexts but not others. The ease of use-usefulness correlation reflected not just statistical association but a causal process, whereby poor usability caused disengagement. Instrumental orientation reflected both rational assessment-focused strategy and pedagogical misalignment between AI and assessment.

Together, Chapters 4 and 5 construct comprehensive understanding of AI's role in first-year Accounting education revealing that AI provides valuable foundational support for conceptual learning and initial confidence-building, particularly for novice learners, but requires substantial enhancement to support comprehensive skill development, diverse learning needs, and seamless integration into assessment-driven educational contexts.

Chapter 6 advances this analysis by interpreting findings through broader theoretical and empirical literature, examining implications for educational practice and institutional policy, and proposing evidence-based recommendations for enhancing AI integration in Accounting education and professional disciplines more broadly. The discussion will synthesise across quantitative and qualitative findings to generate insights transcending the specific case study context, contributing to scholarly understanding of educational AI implementation in resource-constrained, diverse South African higher education environments.

Chapter 6: Understanding the Implications of AI-Enhanced Learning in First-Year Accounting Education

6.1 Introduction

This chapter discusses the findings from the mixed-methods case study examining first-year Accounting students' learning experiences with customised Generative AI resources at Emeritus College. The study addressed three research questions: (1) What are first-year students' learning experiences with AI-generated lecture summaries and pathway questions in ACC1A? (2) How does customised Generative AI shape students' understanding of learning outcomes and skill development? (3) Why do students perceive AI resources as beneficial or challenging?

Chapter 4 presented quantitative findings from 149 students, revealing that while 48-58% perceived AI resources as useful for assessment preparation and conceptual understanding, 40-47% provided neutral responses across multiple constructs, suggesting conditional effectiveness. Strong positive correlations between ease of use and perceived usefulness ($p = 0.692$, $p < 0.01$) demonstrated that usability significantly influenced learning benefits. Students valued AI primarily for instrumental goals, with exam preparation ranking highest (58%), revealing strategic rather than intrinsically motivated learning orientations.

Chapter 5 presented qualitative findings from 14 interviews and 10 focus group participants, illuminating the mechanisms underlying quantitative patterns. Students found AI effective for explaining foundational Accounting concepts and providing initial confidence-building, particularly benefiting novice learners requiring accessible entry points into unfamiliar disciplinary content. However, AI resources focused heavily on declarative knowledge (definitions, concepts, principles) while assessments required procedural knowledge (executing journal entries, preparing financial statements), creating pedagogical misalignment that undermined perceived usefulness.

AI supported lower-order cognitive skills (remembering, understanding, basic application) but neglected higher-order competencies (analysis, evaluation, creation), limiting comprehensive skill development. Usability barriers, mobile-only access creating distraction, interface limitations, inability to copy text, caused premature disengagement even when content quality was high. The theory-practice gap, assessment misalignment, insufficient scaffolding from basic to complex, and lack of

accommodation for diverse learning preferences emerged as critical challenges constraining educational effectiveness.

Synthesising across phases, findings revealed that AI effectiveness was highly conditional, depending on learning stage (initial introduction versus exam preparation), task type (conceptual review versus procedural practice), learner characteristics (novice versus advanced), and integration strategy (supplementary resource versus primary tool). Students demonstrated sophisticated self-monitoring by recognising when AI matched their needs versus when alternative resources were more appropriate, explaining neutral responses. The strong ease of use-usefulness correlation reflected a mechanism whereby usability barriers prevented sustained engagement necessary for experiencing content benefits, not merely statistical association. Students' instrumental orientation reflected both rational response to assessment-driven educational contexts and AI's pedagogical limitations in supporting assessment preparation.

These findings generate implications spanning multiple levels. At the individual level, they illuminate factors mediating AI effectiveness for diverse learners in professional education contexts. At the pedagogical level, they reveal design principles necessary for AI to support comprehensive learning rather than only foundational knowledge acquisition. At the institutional level, they highlight policy considerations for equitable, effective AI integration in resource-constrained South African higher education environments. At the theoretical level, they extend the Technology Acceptance Model and Self-Directed Learning theory while contributing to emerging scholarship on AI in professional disciplines.

This chapter interprets findings through theoretical and empirical lenses, articulates contributions to scholarship, and examines implications for practice, policy, and future research. Section 6.2 interprets key findings through SDL and TAM frameworks, analysing when and why AI supported or hindered learning. Section 6.3 situates findings within empirical literature, identifying convergence with global research while highlighting South African contextual specificity. Section 6.4 develops theoretical contributions, proposing extensions to TAM and SDL theory and presenting an integrated conditional effectiveness framework. Section 6.5 articulates implications for pedagogical design, institutional policy, curriculum development, and faculty support

while identifying productive directions for future research. Section 6.6 synthesises boundary conditions and generalisability considerations. Section 6.7 concludes by reflecting on AI's role in transforming Accounting education in South Africa's evolving higher education landscape.

6.2 Interpretation of Key Findings Through Theoretical Frameworks

This section interprets findings through Self-Directed Learning (SDL) and Technology Acceptance Model (TAM) frameworks established in Chapter 2. Rather than merely restating what students reported, this analysis explains why patterns emerged, what they reveal about AI-enhanced learning, and how they confirm, challenge, or extend theoretical predictions.

6.2.1 AI's Support for Foundational Learning: Strengths and Boundaries

Cognitive Load Theory posits that learning improves when extraneous cognitive load is reduced, enabling efficient use of working memory (Sweller et al., 2011). AI supported foundational understanding by simplifying explanations and making terminology accessible. Quantitative (48% agreement) and qualitative findings confirmed its role in facilitating initial engagement. This aligns with literature highlighting Generative AI's effectiveness in simplifying complex content (Ravselj et al., 2025; Bouteraa et al., 2024; Schei et al., 2024; Chan & Hu, 2023). In South African Accounting education, this reduction in cognitive barriers enables more inclusive access and supports progression to higher-order learning.

Cognitive Mechanisms Underlying Conceptual Support.

AI's effectiveness for foundational learning stems from specific cognitive affordances. First, AI-generated summaries functioned as advance organisers (Ausubel, 1968), providing cognitive structures that helped students organise and integrate new information encountered in lectures and textbooks. For novice learners entering unfamiliar knowledge domains, accessible explanations of core concepts provide essential scaffolding enabling subsequent learning. Students explicitly articulated this: *"When I first started Accounting, I didn't understand the difference between assets and liabilities... The AI summaries broke it down simply"* (Participant #2). This advance organiser function reduced cognitive load (Sweller, 1988) by pre-structuring information, allowing students to focus on comprehension rather than simultaneously determining organisational logic and processing content.

Second, AI resources presented information with high structural clarity including logical sequencing, explicit step-by-step progressions, and predictable formatting. Student appreciation for "how it was organised" and "the logical flow" reflects cognitive load theory's prediction that well-structured materials reduce extraneous load, freeing cognitive resources for germane processing supporting schema construction (Sweller et al., 2011). In contrast, live lectures, constrained by time and classroom dynamics, may deliver content less systematically. AI's algorithmic generation enabled consistently structured explanations unavailable in spontaneous teaching moments.

Third, on-demand availability allowed students to access explanations precisely when knowledge gaps emerged, supporting just-in-time learning. From an SDL perspective, this responsiveness enhanced self-management, students controlled learning timing and pacing without requiring instructor availability Morris (2024). The flexibility to "go through summaries whenever I had free time" enabled learning integration into fragmented schedules, particularly valuable for students who have additional responsibilities outside of their tertiary studies. Thus, the Generative AI tool successfully decreased cognitive load within this context, acting as an enabler for conceptual support (Jose et al., 2025).

Disciplinary and Contextual Significance

While these cognitive mechanisms operate across disciplines, their significance intensifies in South African Accounting education where first-year students encounter persistent challenges conceptualising and mastering foundational concepts (Makhathini et al., 2024; Olifant et al., 2024). The discipline's technical vocabulary, abstract concepts (matching principle, going concern, entity concept), and counterintuitive conventions (debits/credits) create entry barriers. Students from schools with limited Accounting exposure face particularly steep learning curves. AI's accessible explanations may reduce this conceptual gap, potentially contributing to improved retention and reduced time-to-graduation, critical metrics given high dropout rates in Accounting programs (Makhathini et al., 2024).

Moreover, conceptual understanding represents a critical graduate attribute for Accounting professionals expected to provide knowledge-based value in workplace decision-making contexts (Sangster, 2022). While procedural competency (executing bookkeeping tasks) may be increasingly automated, conceptual mastery,

understanding why transactions are recorded in particular ways, how Accounting choices affect financial reporting and when principles apply remains essential for professional judgment. AI support for conceptual foundations potentially strengthens this enduring competency even as procedural tasks become technology mediated.

Critical Evaluation: The Declarative-Procedural Gap

However, enthusiasm for AI's conceptual support requires tempering with critical recognition of its limitations. Anderson's (1983) distinction among knowledge types illuminates the problem between declarative knowledge (factual information, concepts, principles), procedural knowledge (how to perform tasks), and conditional knowledge (when and why to apply procedures). My findings revealed AI effectively supported declarative knowledge. Students learned what concepts meant, but contributed minimally to procedural knowledge mastery. This meant that students were unable to fluently execute Accounting techniques under varied conditions.

The gap identified is pedagogically problematic in professional education. Accounting competence requires not just knowing what journal entries are, but fluently preparing them across diverse scenarios. This includes recognising which accounts are affected, determining debit/credit treatment, and identifying errors. As Participant #13 articulated: "It tells you the steps, which is good, but then you need to practice those steps many times with different examples." Cognitive science literature on skill acquisition demonstrates that expertise develops through extensive, varied practice enabling proceduralisation and transformation of declarative knowledge into automated skills (Anderson, 1983; Ericsson & Pool, 2016). AI resources outlined procedures but provided insufficient practice opportunities for proceduralisation, leaving students conceptually informed but procedurally underprepared.

Moreover, qualitative findings revealed students recognised this limitation, explaining neutral survey responses: "It's good for understanding definitions and basic ideas, but not for learning how to actually do Accounting" (Group C, Student 1). This metacognitive awareness (students accurately assessing AI's boundaries in supporting meaning-making) indicates sophisticated self-monitoring, an SDL competency (Morris, 2024). However, it also reveals that PU remained moderate precisely because conceptual support alone inadequately addressed students' primary need which was passing assessments requiring procedural competency.

The Perceived versus Actual Learning Question

A critical methodological consideration emerges, bearing in mind that this study measured perceived conceptual understanding through self-report, not actual learning outcomes through objective assessment. While 48% agreed AI improved understanding, we cannot conclude it actually did. Educational psychology literature documents imperfect correspondence between metacognitive judgments and objective performance (Dunning et al., 2004). Students may overestimate learning (illusion of competence) or underestimate it (imposter syndrome). The "fluency effect" causes students to mistake the ease of processing clear explanations for genuine understanding (Bjork & Bjork, 2011).

Future research should examine whether students using AI demonstrate superior conceptual understanding on validated assessment instruments compared to matched controls. Do AI users perform better on conceptual questions requiring explanation, analysis, and application of principles? Or does AI create surface familiarity that dissolves under assessment pressure? Without objective outcome data, claims about AI's effectiveness remain tentative, grounded in perceptions that may or may not reflect learning reality.

Theoretical Implications for SDL

From an SDL perspective, AI's foundational support enabled initial self-management, students independently accessed resources, controlled pacing, and initiated learning activities, but did not support full SDL development. Garrison's (1997) SDL model proposes three interdependent dimensions including self-management (planning and executing learning activities), self-monitoring (assessing comprehension and identifying gaps), and intrinsic motivation (internal drive to understand). Morris (2024) extends SDL through four dimensions, control of the learning process, characteristics of the learner, contextual factors and responsibility. The study revealed that AI supported self-management at basic levels but constrained self-monitoring and motivation, owing to contextual factors and learner diversity.

Self-monitoring requires accurate assessment of one's knowledge state. AI pathway questions enabled students to test recall of definitions and basic comprehension, supporting foundational self-monitoring. However, the questions' simplicity, focus on lower-order skills, and occasional grading inaccuracies limited self-monitoring

effectiveness. Students could assess whether they memorised terminology but not whether they developed transferable problem-solving competencies. As Participant #1 noted: "If I got questions wrong about basic concepts, I knew I needed to go back and reread that section." This demonstrates self-monitoring, but only at rudimentary levels.

Intrinsic motivation was constrained by pedagogical misalignment. SDL theory posits that intrinsic motivation, described as a basic human skill, drives sustained autonomous learning (Knowles, 1975) cited in (Morris, 2024). However, when AI resources failed to prepare students for assessments (instrumental goal), intrinsic motivation could not compensate. Students rationally disengaged as described by one of the students *"If the AI questions don't prepare for exam questions, then I'm wasting my time"* (Participant #9). This reveals a tension. SDL theory emphasises intrinsic motivation as ideal, yet professional education contexts create legitimate instrumental motivations. The framework may require adaptation for contexts where external validation (credentials, licensure) provides necessary and appropriate motivation.

Synthesis: Conditional Foundational Support

AI resources provided valuable but bounded foundational learning support. They effectively introduced concepts, reduced initial cognitive barriers, and supported novice learners building disciplinary vocabulary and basic frameworks. This support matters in South African Accounting education where conceptual gaps contribute to high attrition. However, conceptual support without procedural development represents incomplete pedagogy. Students recognised AI's boundaries, explaining neutral perceptions. Future AI must be strategically designed to extend beyond declarative knowledge transmission to support proceduralisation through extensive, varied, progressively challenging practice opportunities aligned with assessment demands (Yuxian, 2025).

6.2.2 The Theory-Practice Gap: Implications for Professional Education

The most substantive pedagogical limitation revealed across both research phases was the theory-practice gap.

Manifestations of the Gap

The theory-practice gap reflects a fundamental limitation. AI excelled at what's computationally easy (generating text explanations, creating simple questions) but

struggled with what's pedagogically necessary (simulating authentic practice contexts, providing nuanced feedback on complex problem-solving). As artificial intelligence scholar Lucy Suchman (2007) argues, AI systems perform well on decontextualised, rule-based tasks but struggle with situated, contextually embedded human activities, precisely what professional practice requires.

Why the Gap Matters: Professional Education Principles

The theory-practice gap is particularly consequential in professional education. Unlike purely academic disciplines where knowledge itself may be the primary learning outcome, professional programs like Accounting prepare students for workplace performance requiring integrated theory-practice competence. Schön's (1983) seminal work on professional education distinguishes "technical rationality" (applying theoretical knowledge to solve well-defined problems) from "reflection-in-action" (improvising responses to ambiguous, complex situations). Accounting demands both; the technical facility with procedures and reflective judgment about their application. Consider an Accountant analysing complex transactions who must fluently execute journal entries without deliberation, allowing focus on judgment calls (how to classify ambiguous items, which disclosure requirements apply). AI that develops conceptual understanding without procedural automaticity leaves students conceptually informed but practically incompetent.

Literature on professional education emphasises apprenticeship models where novices observe, practice, receive feedback, and gradually assume responsibility (Mikkonen et al., 2017). Effective learning sequences move from observation through guided practice to independent application. AI resources jumped from conceptual explanation directly to simple questions, skipping guided practice with varied, progressively challenging problems. Students recognised this as described by Participant #13 *"I need progressively harder questions that build from simple to complex... The AI stayed at the basic level throughout"*.

Constructive Alignment Analysis

Biggs and Tang's (2011) constructive alignment framework provides analytical leverage. Effective education requires alignment among three elements which includes intended learning outcomes (what students should achieve), learning activities (how they'll develop capabilities), and assessment tasks (how achievement

is measured). Misalignment across these elements creates dysfunctional learning systems where students engage in activities that don't develop assessed competencies, as established within the study's findings.

Students rationally responded to this misalignment by abandoning AI for assessment preparation, "Eventually I stopped using the AI for exam prep and focused on past papers and textbook exercises instead, because those actually looked like what I'd face in the exam" (Participant #9). From a TAM perspective, this demonstrates how PU depends on task-technology fit (Goodhue & Thompson, 1995). When AI capabilities didn't align with valued tasks (assessment success), PU declined regardless of conceptual support quality.

Implications for AI Design in Professional Education

These findings have direct implications for designing AI resources in professional disciplines. First, AI cannot remain content-delivery focused; it must provide extensive practice opportunities. This requires moving beyond text generation to incorporate simulations, problem-solving environments, and adaptive practice systems. Technologies such as AI-powered Accounting simulations could present varied transaction scenarios, require student responses, provide immediate feedback, and adapt difficulty based on performance. However, developing such systems requires substantially greater investment than AI-generated summaries.

Second, AI must scaffold from declarative to procedural to conditional knowledge across time. Vygotsky's (1978) Zone of Proximal Development concept suggests effective instruction provides support at the edge of current capability, not far below it. AI that remains at foundational level becomes increasingly insufficient as students develop. Adaptive systems should assess competency continuously and adjust content difficulty, providing challenging problems to advanced learners while offering additional scaffolding to struggling students. My finding that AI's static nature meant declining usefulness over the semester directly supports this design principle.

Third, AI resources must align explicitly with assessment demands. This doesn't mean teaching to the test narrowly, but ensuring practice activities develop competencies that assessments validly measure. If assessments require analysing complex scenarios and making justified Accounting treatment decisions, practice activities must develop these capabilities through progressively complex scenarios requiring analysis

and justification. The pathway questions' focus on recall and comprehension while assessments demanded application, and analysis represents a fundamental misalignment requiring correction.

Fourth, human oversight remains essential. The "human-in-the-loop" principle recognises AI limitations in nuanced judgment, error detection, and pedagogical adaptation (Zanzotto, 2019). Faculty should review AI-generated content for accuracy and pedagogical appropriateness, monitor student performance data to identify where AI support proves insufficient, and intervene with supplementary instruction targeting persistent gaps. AI should augment faculty capacity, not substitute for faculty expertise.

The Expertise Development Perspective

Expertise development research illuminates why theory-practice integration matters. Chi and colleagues' work on knowledge representation reveals that experts organise knowledge around deep principles and can flexibly apply procedures across varied contexts, whereas novices possess fragmented knowledge and struggle to recognise when procedures apply (Chi et al., 1981). Expertise develops through extensive deliberate practice, through goal-directed, feedback-rich engagement with progressively challenging tasks (Ericsson & Pool, 2016).

My findings therefore suggest AI's current implementation provided knowledge that is essential for first-year Accounting students but did not support the practice-based progression through which expertise develops. Future research should examine whether enhanced AI systems, incorporating extensive simulation-based practice, adaptive difficulty, and sophisticated feedback, better support expertise development in Accounting education.

South African Context Considerations

The theory-practice gap has particular implications in South African contexts. First, resource constraints mean institutions may adopt basic AI implementations (chatbots, simple question banks) rather than sophisticated simulation systems. While understandable given funding limitations, this risks providing theory-focused AI that doesn't adequately support professional competency development. Policymakers

must consider whether inadequate AI is worse than no AI, does limited support create illusions of preparedness while failing to develop actual competence?

Second, pedagogical traditions in South African Accounting education vary. Some institutions emphasise theoretical foundations expecting procedural skills to develop in workplaces, while others stress integrated theory-practice from first year. AI integration strategies should align with institutional pedagogical philosophies while meeting professional accreditation requirements. The South African Institute of Chartered Accountants (SAICA) competency framework emphasises both conceptual mastery and practical application; AI resources must support both to align with professional standards.

Third, work-integrated learning opportunities vary across institutions and students. Students with workplace exposure may develop procedural competence through employment even if AI provides only theoretical support, whereas students lacking workplace access depend more heavily on academic experiences for skill development. Equitable AI integration should ensure all students, regardless of extra-academic opportunities, develop requisite competencies.

Synthesis: Beyond Information Transmission

Future AI design must move beyond content delivery to incorporate extensive, varied, progressively challenging practice opportunities with sophisticated feedback, aligned with assessment demands and professional standards. Without such evolution, AI risks becoming an expensive educational supplement providing marginal value rather than a transformative learning tool.

TAM and SDL frameworks provide insights into technology adoption and learner autonomy but do not account for the conditional and dynamic effectiveness observed in this study (Venkatesh & Davis, 2000; Knowles, 1975; Jonassen, 2000). The resultant impact of AI's value varied by learning stage, task type, prior knowledge, and study preferences described in the preceding chapters, manifests itself as technology which was highly effective for some learners and tasks but ineffective for others (Kalyuga et al., 2003; CAST, 2018; Luckin, 2010). TAM typically treats perceived usefulness as static, and SDL assumes learners can effectively self-manage resources, yet neither explains why adoption and impact fluctuate with content complexity, competency level, or learning task. The Extended Technology Acceptance

Model for Education (ETAM-E) in section 6.4 addresses this gap by incorporating task-technology fit, learning-stage sensitivity, learner characteristics, and integration feasibility, while also generating testable hypotheses for adaptive, context-sensitive interventions (Ravselj et al., 2025; Bouteraa et al., 2024; Schei et al., 2024; Chan & Hu, 2023).

Synthesis: Toward a Conditional Effectiveness Framework

A conditional effectiveness framework must specify:

- a) Temporal dynamics: AI's match to learner needs varies across learning progression
- b) Task specificity: AI supports some cognitive operations (comprehension, recall) but not others (application, evaluation)
- c) Individual variation: AI helps some learners (novices, text-oriented, mobile-preferring) more than others (advanced, visual/auditory-preferring, extended-study-oriented)
- d) Systemic integration: AI's value depends on positioning within broader learning ecosystems

From a theoretical standpoint, this conditional effectiveness finding extends TAM by revealing that perceived usefulness is not simply a technology attribute but an emergent property of person-technology-task-context interactions. Future TAM applications in educational settings should model these moderating factors rather than treating usefulness as technology-specific constant.

6.2.3 Usability as Pedagogical Enabler or Barrier

Standard treatments of PEOU in TAM conceptualise it as a correlate of PU, influencing attitudes and behavioural intention (Davis, 1989). This study, however, demonstrates that PEOU functions as a pedagogical gatekeeper, revealing that insufficient usability can prevent engagement entirely, rendering even high-quality content educationally useless. Quantitative findings ($p = 0.692$, $p < 0.01$) indicated a strong PEOU–PU correlation, but qualitative data revealed the underlying mechanism in which usability barriers caused premature disengagement before students could assess content value. For example, Participant #13 noted that mobile-based AI summaries were avoided because the device introduced distracting alternatives, preventing evaluation of the content itself.

Multiple factors contributed to this gatekeeping effect. Mobile-only access introduced attention management challenges, disproportionately affecting students with weaker self-regulation, creating potential equity gaps (Traxler, 2009). Interface limitations, such as poor content organisation, lack of laptop access, and restricted interactivity accumulated, reducing engagement and perceived value. Students also benchmarked institutional AI against commercial tools like TurboLearn and ChatGPT, highlighting that PEOU operates within competitive experiential contexts. Functional constraints, including inability to save or annotate content and lack of progress tracking, further restricted effective use.

These findings extend TAM theoretically by reframing EOU as a necessary condition for usefulness, not merely a correlated predictor. EOU emerges as a multidimensional construct encompassing access, navigation, interaction, and integration ease, each critical for enabling engagement and learning. Furthermore, standards of usability are dynamic, shifting as learners encounter increasingly sophisticated consumer AI (Jonassen, 2000; Luckin, 2010; CAST, 2018). Institutions must therefore view usability as a sustained pedagogical investment rather than a one-time implementation, with ongoing attention to design, functionality, and alignment with student expectations.

Design Implications: Multi-Platform, Intuitive, Interactive

These findings generate clear design imperatives. First, multi-platform availability is essential. Students should access AI via whichever platform suits current context. This could include mobile for brief review during commutes, laptops for extended study sessions, tablets for annotating and note-taking. Flexibility accommodates diverse learning preferences and contexts rather than constraining all students to single modality.

Second, interface design must prioritise intuitiveness. Commercial AI tools provide relevant benchmarks, students expect search functionality, clear navigation, persistent content access, and responsive interactions. Educational AI meeting these standards will be perceived as easy to use; AI falling short will be perceived as inadequate regardless of content quality.

Third, interactivity must be enhanced. Static content delivery represents minimal AI capability. Advanced AI should support dialogic interaction, enabling students to ask questions, AI provided explanations, student request clarification, AI aligned

explanations to student understanding level. This conversational learning aligns with socio-constructivist pedagogy (Vygotsky, 1978) and leverages AI's interactive potential rather than merely using it as text generator.

Fourth, integration with existing learning management systems and productivity tools should be seamless. Students shouldn't need to context-switch between multiple disconnected platforms. AI should embed within LMS environments where students already work, with exports to note-taking applications, connections to digital textbooks, and links to assessment platforms.

Synthesis: Usability as Pedagogical Foundation

The EOU-usefulness relationship revealed in this study demonstrates that usability represents not just user experience concern but pedagogical foundation. Even theoretically sound, content-rich AI resources fail educationally if students don't use them due to usability barriers. This elevates user experience design from aesthetic consideration to educational priority. Institutions investing in AI content development must invest equally in interface design, user testing, and continuous usability refinement. Without such investment, AI's pedagogical potential remains unrealised regardless of content quality.

6.3 Situating Findings Within Empirical Literature

This section positions findings within the broader empirical literature on AI in education, identifying points of convergence with international research while highlighting context-specific patterns that may reflect South African higher education's unique characteristics. The analysis moves beyond simple confirmation to examine why certain findings align with prior work while others diverge, generating insights about generalisability and contextual boundary conditions.

6.3.1 Convergence with Global AI in Education Research

Conceptual Learning Support

My finding that AI effectively supported foundational conceptual understanding converges strongly with international literature. Ravselj et al.'s (2025) global study across 109 countries identified that students in applied sciences (including Accounting, Engineering, and technical fields) experienced increased satisfaction with AI tools, attributing this to AI's capacity for simplifying complex disciplinary content. Similarly,

Bouteraa et al. (2024) in healthcare education and Chan & Hu (2023) in business education document AI's effectiveness for summarising extensive content and clarifying difficult concepts. This convergence suggests AI's conceptual support function operates consistently across educational contexts, cultures, and disciplinary domains.

The mechanism likely explains this consistency. AI excels at information organisation, synthesis, and clear presentation, capabilities useful wherever students encounter complex, unfamiliar content. Unlike culturally specific or context-dependent educational interventions whose effectiveness varies across settings, AI's text processing and generation capabilities function similarly regardless of where students are located. This suggests conceptual support may represent AI's most reliable, generalisable educational contribution.

However, convergence regarding conceptual support should not obscure a critical gap. Most existing studies, including those cited above, measure student satisfaction and PU rather than actual learning outcomes through validated assessments. My study shares this limitation. The field collectively demonstrates students perceive AI as conceptually helpful but lacks robust evidence that AI actually improves conceptual understanding measured objectively. This represents an urgent research gap requiring experimental or quasi-experimental designs comparing learning outcomes between AI users and carefully matched control groups.

Technology Acceptance Model Confirmation

My quantitative finding that EOU strongly predicts PU aligns with extensive TAM literature spanning multiple educational contexts (Tiwari et al., 2023; Venkatesh & Davis, 2000). This convergence validates TAM's core theoretical predictions while my qualitative findings extend TAM by revealing mechanisms, such as usability barriers which cause premature disengagement, preventing usefulness evaluation. The mechanism identified positions usability as a gateway rather than merely correlated predictor, representing a theoretical extension not fully articulated in prior TAM literature, suggesting how case-study designs can refine theory even when quantitative patterns confirm prior findings.

My finding that PU mediates adoption also confirms TAM, but with important qualitative nuancing. The study revealed that usefulness perceptions varied by task type, learning

stage, and individual characteristics, revealing conditional rather than uniform effects. This contextual dependency suggests future TAM applications should model moderating variables rather than treating usefulness as a technology attribute alone.

Instrumental Orientation in Assessment-Driven Contexts

Students' primary valuation of AI for exam preparation (58%) aligns with substantial literature documenting instrumental orientations in higher education (Bosch et al., 2023; Muringa, 2025). This convergence is theoretically meaningful as it suggests instrumental motivation predominates broadly in higher education contexts where progression, graduation, and career access depend on assessment performance. The consistency across studies and contexts indicates this represents systemic feature of credentialing systems rather than local cultural phenomenon.

However, my finding that instrumental and intrinsic motivations can coexist, students valued AI both for exam preparation and conceptual understanding, adds nuance to literature sometimes positioning these motivation types as opposing. Students simultaneously pursued strategic assessment success and genuine understanding, recognising that in professional education, assessment requiring deep comprehension makes intrinsic learning instrumentally valuable. This suggests motivation scholarship should conceptualise instrumental and intrinsic as overlapping rather than mutually exclusive categories.

Usability as Critical Adoption Factor

Extensive literature identifies usability as crucial for technology adoption (Venkatesh et al., 2003). My findings converge while specifying particular usability dimension implications for educational AI. These include platform flexibility (mobile versus desktop access), interface intuitiveness compared to consumer AI standards, and functional capabilities (copy/paste, search, save). This specification provides actionable design guidance beyond general usability principles.

My finding that students compared institutional AI unfavourably to commercial tools adds to emerging literature on "AI natives," students entering higher education with extensive prior AI exposure who benchmark educational AI against sophisticated consumer applications (Moore & Lookadoo, 2024). This convergence suggests institutions globally face similar challenges, with trends indicating that student

expectations are shaped by ChatGPT, Claude, Gemini, and specialised tools which create demanding standards for educational AI competing in crowded technology ecosystem.

6.3.2 Divergence and Contextual Specificity: South African Considerations

Digital Infrastructure Constraints

While international literature emphasises AI's potential for expanding access and supporting diverse learners (Holmes et al., 2019), my findings revealed usability barriers potentially exacerbating inequity, particularly mobile-only access creating engagement challenges. This partial divergence may reflect South African context where many students' primary or sole internet access occurs via mobile devices with limited data plans. International AI research often implicitly assumes students possess laptops with reliable connectivity; this assumption doesn't hold universally in South African contexts.

However, my single-campus sample limits conclusions. Pietermaritzburg students may differ from urban campus students with better technology access. Future research should examine cross-campus variation in AI experiences, hypothesising that resource-constrained campuses face greater usability challenges while well-resourced institutions encounter fewer access barriers. Such research would clarify whether usability issues I identified reflect general South African patterns or specific campus contexts.

Theory-Practice Gap Intensity

While literature broadly recognises challenges integrating theory and practice in professional education (Schön, 1983), the intensity of pedagogical misalignment in my findings may exceed typical patterns. Qualitative accounts described profound dissatisfaction with AI's procedural knowledge support, contributing substantially to neutral overall perceptions. This may reflect disciplinary specificity, in which Accounting requires particularly high proceduralisation levels, students must execute complex multi-step procedures fluently. In disciplines where conceptual understanding suffices (philosophy, literature) or procedures are simpler (basic mathematics), theory-practice gaps may create less dissatisfaction.

Alternatively, this may reflect AI implementation quality. Perhaps more sophisticated AI systems in better-resourced contexts provide better procedural support through simulations and adaptive practice. My study examined a relatively basic implementation (AI-generated summaries and simple questions). Findings may not generalise to implementations using advanced AI capabilities.

Additionally, South African Accounting education's particular emphasis on practical competence, driven by SAICA accreditation requirements and industry expectations for work-ready graduates, may intensify theory-practice gap salience compared to contexts with different professional expectations. Comparative research across educational systems with varying professional education philosophies could illuminate whether theory-practice gaps represent universal challenges or context-specific concerns.

Prior AI Experience Patterns

My finding that 89.9% of students had prior AI experience aligns with studies documenting widespread AI familiarity among university students (Ravselj et al., 2025), but the implications may differ across contexts. International literature often portrays AI exposure positively, assuming familiarity facilitates educational adoption. My findings illuminate complexity, revealing that prior experience created high expectations that institutional AI failed to meet, potentially undermining adoption. Students didn't lack AI familiarity; rather, familiarity with sophisticated consumer AI made institutional AI seem inadequate by comparison.

This suggests contextual factors worth exploring. In contexts where students lack prior AI experience, institutional AI may represent novel, impressive technology readily adopted. Where students extensively use consumer AI, institutional AI faces higher adoption thresholds. Literature should examine how prior experience moderates AI adoption in educational settings, potentially revealing curvilinear relationship, whereby moderate prior experience optimises adoption (students comfortable with AI but not highly demanding), while very low or very high prior experience creates adoption challenges.

6.3.3 Contributions to Accounting Education Literature

This study advances Accounting education scholarship by providing empirical evidence regarding AI integration in first-year courses, addressing calls for research on digital transformation in Accounting curricula (Muller, 2025; Cudia et al., 2024). Existing literature extensively documents industry AI adoption, automated bookkeeping, predictive analytics, fraud detection, but provides limited evidence on educational integration effectiveness (Landsberg & van den Berg, 2023). My study fills this gap with detailed examination of student experiences, revealing both potential and limitations.

The finding that AI supported conceptual understanding suggests potential for addressing persistent challenges first-year students face with Accounting fundamentals (Makhathini et al., 2024; Olifant et al., 2024). High dropout rates and extended timelines in Accounting programs partially stem from conceptual barriers AI might help overcome. However, the finding that AI inadequately developed procedural competence reveals current implementations insufficiently prepare students for SAICA competency framework requirements, emphasising both conceptual mastery and practical application.

These findings position AI as potentially valuable supplementary resource but insufficient as primary pedagogical approach, at least in current implementations. The field should investigate whether enhanced AI incorporating simulations, adaptive practice, and sophisticated feedback better supports comprehensive Accounting competence or whether fundamental AI limitations constrain effectiveness regardless of sophistication.

My integration of SDL and TAM frameworks contributes theoretically to Accounting education literature, which has applied these frameworks separately but rarely in combination. The finding that instrumental and intrinsic motivation coexist challenges simplified characterisations of Accounting students as purely grade-focused. This nuance matters for pedagogical design, implying that rather than attempting to eliminate instrumental motivation, educators can leverage it through constructive alignment ensuring deep learning becomes instrumentally valuable.

The conditional effectiveness framework developed from findings provides practical guidance for Accounting educators considering AI adoption. Rather than asking

whether to adopt AI (binary choice), the framework enables more nuanced decisions, advocating for the adoption of AI for specific purposes (foundational concept introduction, confidence-building), with particular student populations (novices, conceptually-struggling learners), integrated strategically with traditional resources (textbooks, practice exercises, faculty support). This specification advances beyond enthusiastic endorsement or sceptical rejection toward evidence-based, contextually-appropriate adoption.

Finally, the study's South African focus contributes to underrepresented literature. Most Accounting education research occurs in North American, European, or Australian contexts. My findings reveal both similarities (conceptual support value, instrumental orientations) and potential differences (infrastructure constraints, theory-practice gap intensity) warranting further research. Building South African evidence base enables contextually-appropriate policy and practice rather than uncritical adoption of international best practices that may not transfer to local conditions.

Synthesis: Integration and Contextual Boundaries

Situating findings within empirical literature reveals meaningful convergence on several dimensions, AI's conceptual support value, TAM confirmation, instrumental orientations, usability importance, suggesting these represent relatively robust, generalisable patterns. Divergence and contextual specificity emerged around infrastructure constraints, theory-practice gap intensity, and prior experience implications, suggesting these may vary based on educational system characteristics, disciplinary requirements, technological contexts, and implementation quality.

This pattern of convergence and divergence has theoretical implications. Some educational phenomena appear universal (or at least broadly generalisable), while others depend substantially on context. Literature development should prioritise identifying which findings generalise and which require contextual specification. My study contributes evidence toward this synthesis while acknowledging limitations preventing definitive generalisability claims, single institution, single semester, relatively small qualitative sample. Future research should conduct cross-institutional, longitudinal, and comparative studies generating robust understanding of AI's potential and limitations across diverse contexts.

6.4 Theoretical Contributions and Extensions

This section develops theoretical contributions emerging from empirical findings, proposing extensions to Technology Acceptance Model and Self-Directed Learning theory while presenting an integrated conditional effectiveness framework for AI-enhanced learning. Rather than merely applying existing theories to interpret findings, this analysis demonstrates how findings challenge, refine, and extend theoretical understanding.

6.4.1 Extending Technology Acceptance Model for Educational Contexts

TAM provides valuable explanatory power for technology adoption but requires refinement for educational applications. My findings reveal three specific extensions warranting theoretical development.

Extension 1: Disaggregating Perceived Usefulness by Knowledge Type

TAM conceptualises perceived usefulness as a unidimensional construct, meaning the degree to which technology improves performance on valued tasks (Davis, 1989). My findings reveal that in educational contexts, usefulness must be disaggregated by knowledge type supported. Students perceived AI as useful for declarative knowledge acquisition (learning definitions, understanding concepts) but not for procedural knowledge development (executing Accounting procedures fluently) or conditional knowledge application (knowing when and why to apply procedures). This created mixed overall usefulness perceptions, students valued AI for some learning outcomes but not others.

This disaggregation has theoretical significance. It suggests perceived usefulness in education represents multidimensional rather than unidimensional construct. Educational technologies may excel at supporting certain learning outcomes while proving inadequate for others, creating complex usefulness profiles rather than simple useful/not useful dichotomies. Future TAM applications should model usefulness dimensionally, perhaps adapting Anderson's (1983) knowledge taxonomy through levels of acquisition, application and development (ie. usefulness for declarative knowledge acquisition, usefulness for procedural knowledge development, usefulness for knowledge application and usefulness for metacognitive skill development).

This extension enables more precise understanding of when and why educational technologies prove valuable, moving beyond aggregate usefulness measures toward learning outcome-specific evaluations.

Extension 2: Ease of Use as Pedagogical Gatekeeper

TAM positions EOU as influencing PU through cognitive effort calculations, meaning that difficult technology diverts cognitive resources from tasks to navigation (Davis, 1989). My findings reveal a more fundamental mechanism. Insufficient EOU prevents technology usage entirely, eliminating opportunity for usefulness evaluation. This elevates EOU from adoption predictor to pedagogical gatekeeper, necessary condition for educational effectiveness regardless of content quality.

Traditional TAM conceptualises the EOU usefulness relationship as mediated by cognitive effort and moderated by experience. I propose a direct pathway as follows, inadequate EOU results in non-use, ultimately materialising as no pedagogical value realised. This reconceptualisation has practical implications. It suggests that in educational technology development, usability cannot be addressed after content development as a secondary concern; rather, usability must be foundational priority determining whether content ever reaches learners.

Moreover, my findings revealed EOU encompasses multiple dimensions requiring separate consideration pertaining to ease of access, navigation, interaction and integration (as discussed earlier in this section). Educational TAM applications should therefore disaggregate ease of use dimensionally to identify specific usability bottlenecks rather than treating ease as monolithic construct.

Extension 3: Task-Technology Fit as Central Mediator

TAM implicitly assumes that if technology is easy to use and perceived as useful generally, adoption follows. My findings, however, demonstrated that task-technology fit (Goodhue & Thompson, 1995), alignment between technology capabilities and task requirements, critically mediates the EOU, usefulness, adoption relationship. Students found AI easy to use (when they used it) and useful for certain tasks (conceptual review), but adoption for high-stakes tasks (exam preparation) remained low because AI capabilities didn't align with assessment demands.

This suggests an integrated model positioning task-technology fit as a central mediating variable as depicted in Figure 29:

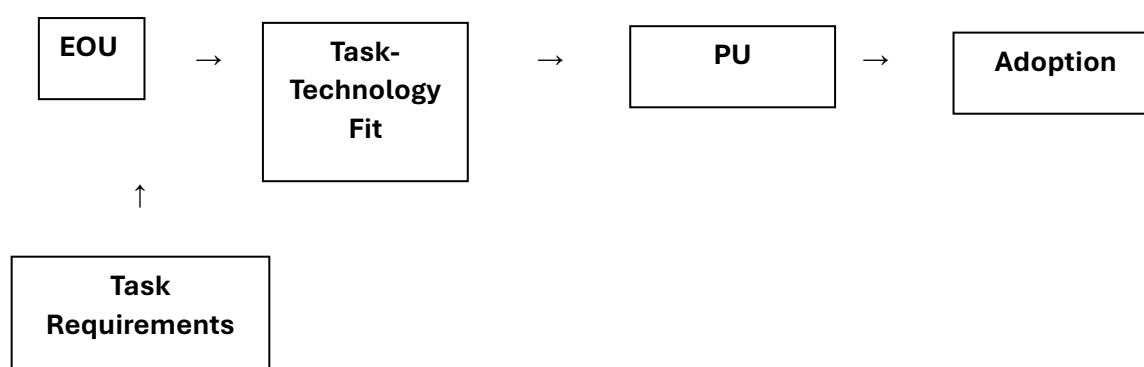


Figure 29: Integrated model (task-technology as central mediating variable) (Author collation)

Task-technology fit depends on the match between what technology supports and what tasks require. In education, critical tasks include assessment preparation, skill development, and knowledge application. When technology-task fit is high (AI capabilities match task requirements), usefulness is perceived and adoption follows. When fit is poor (AI supports only a subset of task requirements), PU declines and adoption falters despite EOU.

This extension has significant implications. It suggests educational technology designers cannot focus solely on improving technology; they must understand learning task structures, assessment demands, and performance criteria. Technology optimised for wrong tasks, no matter how sophisticated, will fail to achieve educational adoption.

Proposed Extended TAM for Education (ETAM-E)

Synthesising these extensions, I propose an Extended Technology Acceptance Model for Education (ETAM-E):

Core Propositions:

P1: Perceived usefulness in educational contexts is multidimensional, varying by learning outcome type (declarative, procedural, conditional knowledge)

P2: Ease of use functions as pedagogical gatekeeper; below threshold levels, educational value cannot be realised regardless of content quality

P3: Task-technology fit mediates the EOU → PU relationship. Technologies may be easy to use but perceived as useless if capabilities don't align with valued learning tasks

P4: Educational technology adoption depends on integration feasibility within existing learning ecologies; standalone tools requiring ecosystem disruption face adoption barriers regardless of EOU and PU

P5: Individual learner characteristics (prior knowledge, learning preferences, self-regulation capacity) moderate all relationships; no universal adoption patterns exist

Testable Hypotheses:

H1: Educational technologies supporting multiple knowledge types (declarative + procedural + conditional) will demonstrate higher overall PU than technologies supporting single knowledge type)

H2: Usability improvements below threshold levels will increase adoption more than usability improvements above threshold levels (diminishing returns)

H3: Task-technology fit will mediate the EOU → PU relationship; the indirect effect through fit will exceed the direct effect

H4: Technologies requiring minimal learning ecology disruption will achieve higher adoption than technologies requiring substantial ecosystem changes, controlling for EOU and PU

H5: The EOU and PU adoption pathway will vary significantly across student subgroups defined by prior knowledge, learning preferences, and self-regulation capacity

This extended model provides richer conceptual framework for understanding educational technology adoption while generating testable hypotheses for future research. It moves TAM beyond generic technology acceptance toward education-specific theorising recognising learning's complexity and diversity.

6.4.2 Refining Self-Directed Learning Theory for Technology-Enhanced Professional Education

SDL theory provides a valuable framework for understanding autonomous learning but requires refinement when applied to technology-enhanced professional education contexts. My findings revealed three tensions requiring theoretical attention.

Tension 1: Context-Appropriate SDL Expectations

SDL theory emerged from adult education contexts emphasising voluntary, self-motivated learning among mature learners (Knowles, 1975). My findings involved 18-21 year-old students in structured degree programs with prescribed curricula, mandatory assessments, and external accountability. This context creates different SDL dynamics than adult education settings SDL theory originally addressed.

Students exhibited some SDL dimensions, self-management through independent resource use, self-monitoring of foundational knowledge, but operated within heavily structured institutional contexts constraining autonomy. They didn't choose to study Accounting from intrinsic interest (many reported); they enrolled because professional credentials require it. They didn't select learning activities freely; they followed prescribed curriculum preparing for mandatory assessments.

This raises a theoretical question, should SDL expectations differ across educational contexts? I propose context-appropriate SDL framework recognising that autonomous learning operates differently in professional education than adult education:

Adult Education SDL (Knowles's original context):

- Voluntary participation driven by intrinsic interest
- Self-selected learning goals and content
- Flexible timelines and pacing
- Intrinsic motivation predominates

Professional Education SDL (my study's context):

- Mandatory participation driven partially by credentialing needs
- Externally-defined learning outcomes with constrained choices
- Fixed timelines and assessment schedules

- Instrumental and intrinsic motivation coexist

Rather than judging professional education students as insufficiently self-directed because they exhibit instrumental motivation and operate within constraints, theory should recognise context-appropriate SDL manifestations. Professional education SDL involves autonomy within structure. Students manage learning activities independently (self-management), monitor progress against external standards (self-monitoring), and develop motivation blending instrumental and intrinsic elements (adaptive motivation).

Tension 2: Developmental Progression versus Immediate Autonomy

SDL theory often implies learners should exhibit autonomous behaviour immediately. My findings suggested many first-year students lacked SDL readiness, they struggled to determine when to use AI versus other resources, how to integrate multiple tools effectively, and whether they understood sufficiently for exam success. This finding advocates for the gradual development of SDL through a scaffolded approach.

I therefore propose a scaffolded SDL framework (Figure 30) recognising that autonomous learning capacity develops progressively:

Phase 1: Guided Practice (1st Year, 1st Semester) - Faculty provide explicit guidance on resource selection, study strategies, self-assessment methods - Structured scaffolding supports initial self-management and self-monitoring attempts - Instrumental motivation acknowledged as legitimate starting point	Phase 2: Supported Autonomy (1st Year, 2nd semester into 2nd Year) - Scaffolding gradually withdrawn as students demonstrate competence - Students assume increasing responsibility for learning decisions with available support - Intrinsic motivation cultivated through experiences of competence and mastery	Phase 3: Independent Self-direction (3rd Year onward) - Students autonomously manage learning with minimal guidance - Self-monitoring becomes accurate and sophisticated - Intrinsic motivation sustains engagement
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Figure 30: Proposed SDL framework to develop autonomous learning capacity

This developmental framework acknowledges that expecting immediate, full SDL from first-year students may be unrealistic. Instead, institutions should scaffold SDL development, teaching self-direction skills explicitly rather than assuming students

possess them naturally. AI resources should support this progression by providing more structure and guidance initially, gradually increasing learner control and requiring more autonomous decision-making as students develop SDL capacity.

Tension 3: Technology's Double-Edged SDL Impact

My findings indicate that technology both supported and constrained SDL. On-demand AI access enhanced self-management by reducing dependence on instructor availability, yet poor usability and device-based distractions introduced friction that undermined autonomous learning. SDL emphasises learner control over activities (Knowles, 1975), but effective control requires low-friction access to resources. Complex navigation, multiple passwords, or repeated device switching diverted cognitive resources from learning to logistics, limiting self-management. Additionally, distractions inherent in mobile devices (notifications, app switching, social media) imposed extra self-regulation demands, a key SDL prerequisite (Zimmerman, 2002). Poor feedback accuracy and pedagogical misalignment further constrained students' ability to monitor progress and sustain intrinsic motivation, highlighting that technology can simultaneously enable and hinder SDL development.

This suggests technology-enhanced SDL requires careful design consideration. Figure 31 describes how technologies supporting SDL should be positioned to develop self-management, self-monitoring and motivation.

Self-management	Self-monitoring	Motivation
- Provide flexible, on-demand access accommodating diverse schedules and preferences - Offer multiple pathways through content allowing learner choice - Enable pace control without institutional scheduling constraints	- Provide accurate, immediate feedback on performance - Help students calibrate self-assessments against objective standards - Make learning progress visible through dashboards, analytics, achievement tracking	- Connect learning activities to authentic problems and professional practices - Provide appropriate challenge levels (neither too easy nor overwhelming) - Incorporate intrinsically interesting elements (exploration opportunities, discovery experiences, creative applications) - Transparently link learning to valued outcomes (competence, career success, personal growth)

Figure 31: Proposed technology-enhanced framework to support SDL

Technologies failing in any dimension undermine SDL development. My findings revealed AI supported self-management partially but constrained self-monitoring and motivation, limiting overall SDL effectiveness.

Proposed SDL Framework for Technology-Enhanced Professional Education

Synthesising these tensions, I propose a refined SDL framework as follows:

Principle 1: Context-Appropriate Autonomy

SDL manifestations vary across educational contexts. Professional education SDL involves autonomy within institutional structures rather than complete learner control.

Principle 2: Developmental Progression

SDL capacity develops over time with explicit scaffolding. Institutions should teach self-direction skills systematically rather than assuming pre-existing competence.

Principle 3: Motivation Spectrum

Instrumental and intrinsic motivation represent spectrum endpoints rather than opposites. Professional education legitimately incorporates both; effective pedagogy leverages instrumental goals to cultivate intrinsic interest.

Principle 4: Technology as SDL Enabler and Constraint

Technology can enhance SDL by supporting self-management, self-monitoring, and motivation, but only when designed intentionally for SDL support. Technology lacking these design features may constrain SDL despite seeming to increase learner autonomy.

Principle 5: Individual Variation

Students vary in SDL readiness, requiring differentiated support. Universal approaches assuming uniform SDL capacity create inequitable outcomes.

This refined framework provides more nuanced guidance for supporting SDL in contemporary technology-enhanced professional education contexts than original SDL theory developed for adult education settings.

6.4.3 Constructivism and AI: Tensions and Possibilities

My findings revealed tensions between AI-enhanced learning and constructivist pedagogical principles. Constructivism emphasises active knowledge construction through learner-directed exploration, social interaction, and authentic problem-solving (Bransford et al., 2000; Vygotsky, 1978). AI resources in my study provided largely passive content consumption rather than active construction, raising questions about AI-constructivism compatibility.

Tensions Identified

Passivity versus Activity:

AI summaries and questions positioned students as information receivers rather than active knowledge constructors. Students read explanations and answered questions but didn't engage in discovery, problem-posing, or creative application. This contradicts constructivist emphasis on learning through doing, experimenting, and constructing understanding actively.

Predetermined versus Emergent:

AI content was predetermined, offering identical information to all students regardless of their interests, questions, or confusion points. Constructivism values emergent learning responsive to learner needs and curiosities. While students could choose when to access AI, content itself remained static rather than adapting to individual construction processes.

Individual versus. Social:

Students engaged with AI individually through mobile devices, lacking social construction opportunities. Constructivism emphasises learning through dialogue, collaboration, and negotiation of shared meaning (Vygotsky, 1978). AI's solitary usage pattern missed these benefits.

Possibilities for Constructivist AI

However, tensions don't imply incompatibility. AI could support constructivist learning if designed appropriately:

Interactive Problem-Solving Environments:

Rather than delivering information, AI could present authentic problems requiring students to construct solutions. For example, Accounting AI could provide business scenarios requiring students to determine appropriate Accounting treatment, record transactions, and justify decisions. AI would provide feedback and scaffolding rather than direct instruction.

Adaptive Questioning:

AI could engage students in Socratic dialogue, posing questions that provoke thinking rather than providing answers. When students express confusion, AI could ask guiding questions helping students construct understanding rather than explaining directly.

Collaborative AI:

AI could facilitate peer collaboration by connecting students working on similar problems, suggesting collaboration opportunities, or moderating peer discussion. Rather than replacing social learning, AI could enhance it through intelligent grouping and interaction support.

Exploratory Tools:

AI could provide simulations, data sets, and modeling tools enabling exploration and experimentation. Students would manipulate variables, observe consequences, and construct understandings of relationships rather than reading about them.

These possibilities require substantially more sophisticated AI than simple content delivery systems. However, they demonstrate that AI-constructivism tensions reflect current implementation limitations rather than fundamental incompatibility.

6.4.4 Toward an Integrated Conditional Effectiveness Framework

Synthesising findings and theoretical extensions, I propose an Integrated Conditional Effectiveness Framework for AI-Enhanced Learning (ICEFL). This framework specifies conditions determining when AI supports learning effectively and when it proves inadequate, integrating TAM, SDL, and constructivism insights.

Framework Components

The framework comprises four interacting components as described in Figure 32:

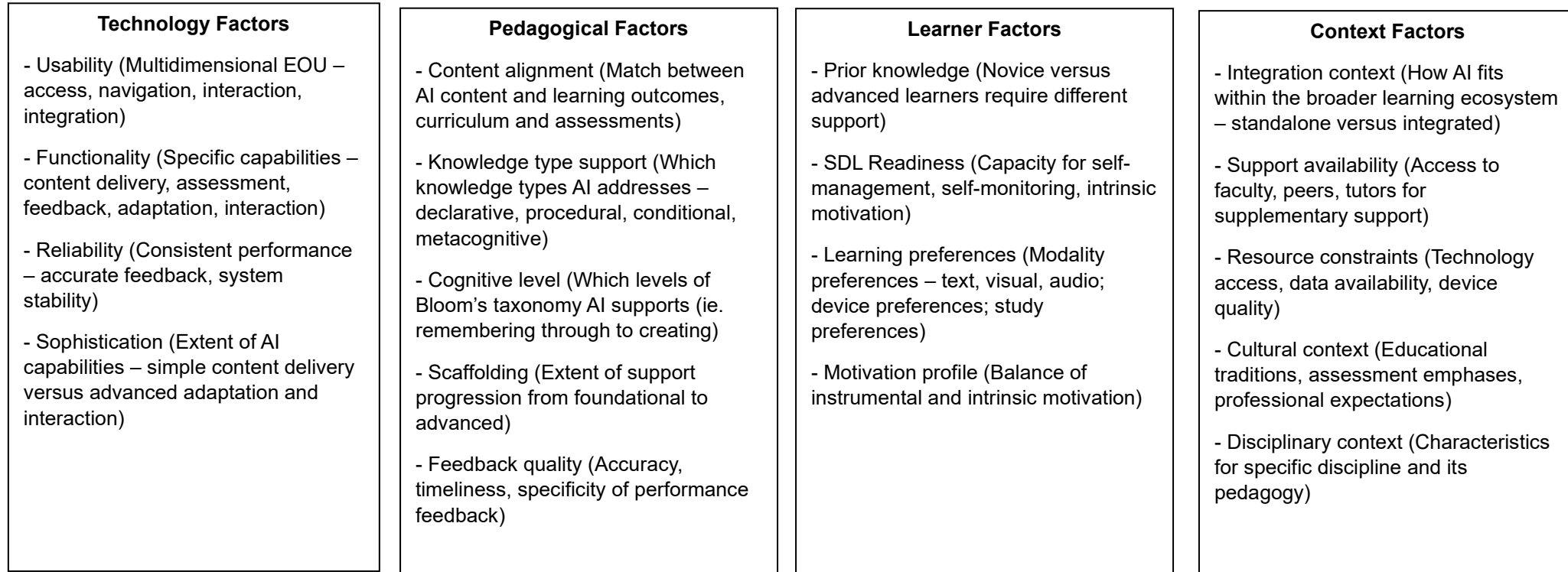


Figure 32: Integrated Conditional Effectiveness Framework for AI-Enhanced Learning (ICEFL)

Conditional Effectiveness Predictions

The framework predicts AI effectiveness through interactions among components:

High effectiveness conditions (High usability + High content alignment + Novice learners + Integrated use + Adequate support). Example, user-friendly AI with assessment-aligned content used by first-time Accounting learners as supplement to lectures and practice exercises with faculty support available.

Moderate effectiveness conditions (Moderate usability + Partial content alignment + Mixed learner levels + Strategic use + Limited support). Example, basic AI tool with foundational content useful for concept introduction but not exam preparation, used selectively by students with varying backgrounds.

Low effectiveness conditions (Low usability + Poor content alignment + Advanced learners + Standalone use + Minimal support). Example, difficult-to-access AI with basic content misaligned to assessment demands, used by advanced students as primary resource without faculty guidance.

Negative effectiveness conditions (Any critically low factor). Example, complete usability failure, total misalignment, extreme resource constraints) makes AI ineffective regardless of other factors.

The framework emphasises interactions, high performance on some factors cannot fully compensate for failures on others. Pedagogically excellent content proves useless if unusable. Highly usable AI proves ineffective if pedagogically misaligned. Student motivation cannot overcome fundamental AI limitations.

Framework Applications

This framework provides practical guidance for design decisions, such as which factors require priority investment. The framework suggests usability and pedagogical alignment represent minimum thresholds requiring attention before sophistication enhancements. Secondly, implementation decisions, such as which learners, courses, and purposes should AI be implemented for. The framework enables targeting AI to contexts predicting effectiveness rather than universal deployment. Thirdly, evaluation decisions, such as how should AI effectiveness be assessed. The framework suggests multifactor evaluation rather than single outcome measures, examining whether AI meets conditional effectiveness criteria. Fourthly the framework suggests research directions, in terms of what remains unknown. The framework identifies gaps requiring investigation such as interactions among

factors, threshold levels determining effectiveness and temporal dynamics as factors evolve.

Theoretical Contribution

This integrated framework advances educational AI scholarship by moving beyond binary effectiveness questions ("does AI work?") toward conditional understanding ("when, why, for whom, and under what circumstances does AI support learning?"). It synthesises multiple theoretical perspectives, TAM's technology focus, SDL's learner focus, constructivism's pedagogical focus, into coherent predictive model. It balances generality (applicable across contexts) with specificity (identifying factors requiring contextual assessment).

Future research should test framework predictions through studies manipulating framework factors systematically and measuring impacts on learning outcomes. Such research would refine factor definitions, identify critical interaction patterns, and establish evidence-based guidelines for AI integration in education.

6.5 Implications for Practice, Policy, and Future Research

This section articulates implications spanning pedagogical design, institutional policy, curriculum development, faculty support, and future research directions. Rather than generic recommendations, these implications provide specific, evidence-based guidance grounded in study findings.

6.5.1 Pedagogical Design Principles for AI Integration

Findings generate specific design principles for developing educationally effective AI resources.

Principle 1: Scaffold from Foundational to Advanced Across Semester

The study found that AI's static foundational focus proved increasingly insufficient as students advanced. Students valued AI initially but found it inadequate later.

Design specification for scaffolding:

- Week 1-3: Definitional questions, basic concept explanations, single-concept application
- Week 4-6: Multi-step procedural problems, integrated concept application, error identification
- Week 7-8: Complex authentic scenarios, analytical judgment questions, synthesis tasks requiring integration across topics

- Week 9-12: Advanced applications, creative problem-solving, evaluation and justification tasks

Implementation requirements to support diversity in students' learning aptitude:

- Content library spanning difficulty levels
- Assessment algorithms determining student competency and assigning appropriate difficulty
- Faculty oversight identifying students struggling with progression and providing intervention

Principle 2: Integrate Theory and Practice Systematically

The study identified that the theory-practice gap represented the primary pedagogical limitation undermining effectiveness.

Design specification for theory and practice integration:

- For each concept, provide: (1) theoretical explanation, (2) worked example demonstrating application, (3) practice problem with scaffolding, (4) similar problem without scaffolding, (5) extension problem requiring adaptation
- Ensure a 2:1 practice-to-theory ratio minimum; students need extensive practice
- Include common error demonstrations showing what mistakes look like and why they're incorrect

Implementation requirements to maintain the minimum practice-to-theory ratio:

- Accounting expertise to develop realistic scenarios
- Sufficient practice problems ensuring varied exposure
- Feedback explaining not just correct answers but reasoning processes

Principle 3: Align Explicitly with Assessment Demands

The study uncovered a misalignment between AI practice and assessment demands caused students to abandon AI for exam preparation.

Design specification for assessment alignment:

- Map all AI content and questions to assessment task types
- Ensure practice question format, complexity, and cognitive demands match assessment

- Provide timed practice simulating assessment conditions
- Include complete practice exams mirroring actual exam structure

Implementation requirements for explicit assessment alignment:

- Access to past assessments and assessment blueprints
- Regular updating as assessments evolve
- Faculty validation ensuring alignment accuracy

Principle 4: Accommodate Diverse Learning Needs

The study identified that visual, auditory, and kinaesthetic learners struggled with text-only format. Mobile-only access suited some students but not others.

Design specification for diversity accommodation:

- Provide multiple content representations (text explanations, diagram illustrations, video demonstrations, interactive simulations)
- Offer platform flexibility (mobile app, desktop website, tablet optimisation)
- Enable content customisation (font size, colour schemes, read-aloud functionality)
- Support varied interaction modes (reading, listening, manipulating, creating)

Implementation requirements for the accommodation of diverse learning needs:

- Multimedia development capacity
- Universal Design for Learning expertise
- Accessibility testing with diverse learners

Principle 5: Enable Accurate Self-Monitoring

The foundational basis for this principle resides in the study's finding which indicated that inaccurate automated grading undermined self-monitoring. Simple questions provided inadequate assessment of deeper understanding.

Design specification to support self-monitoring:

- Develop sophisticated natural language processing recognising semantically equivalent responses
- Provide immediate, specific feedback explaining why answers are correct/incorrect

- Include confidence ratings allowing students to indicate uncertainty
- Offer diagnostic assessments identifying specific knowledge gaps
- Visualise progress across learning outcomes and competency dimensions

Implementation requirements for effective self-monitoring:

- Advanced AI grading capabilities
- Faculty review of flagged responses students contest
- Learning analytics infrastructure tracking student progress

Principle 6: Provide Human-in-the-Loop Support

Findings reveal that students valued AI accessibility but recognised limitations requiring human judgment, particularly for complex or contested responses.

Design specification for human-in-the-loop integration:

- AI provides initial feedback and explanations
- Students can flag responses for faculty review
- Faculty monitor AI interaction data identifying where students struggle
- Faculty provide supplementary instruction targeting common AI-identified gaps
- Regular faculty review of AI content ensuring accuracy and currency

Implementation requirements:

- Learning management system integration enabling faculty oversight
- Analytics dashboards highlighting student difficulties
- Faculty time allocated for AI monitoring and support

6.5.2 Institutional Policy Recommendations

Findings reveal institutional policy needs for equitable, effective AI integration.

Policy 1: Establish AI Quality Assurance Processes

Rationale: AI-generated content requires validation for accuracy, pedagogical appropriateness, and alignment with learning outcomes.

Specific recommendations:

- Require faculty approval of AI content before student access

- Implement alignment matrices documenting connections between AI activities, learning outcomes, and assessments
- Conduct mid-semester student experience surveys identifying misalignments
- Analyse end-of-semester performance data comparing sections using AI versus not using AI
- Establish cross-institutional communities of practice sharing effective AI integration strategies

Implementation: Integrate quality assurance mechanisms into existing course approval. Require AI alignment documentation in course outlines.

Policy 2: Ensure Equitable Technology Access

Rationale: Mobile-only access, data costs, and device limitations created equity barriers. Single-platform implementation advantages some students while disadvantaging others.

Specific Recommendations:

- Provide multi-platform access (mobile, desktop, tablet) for all AI resources
- Offer on-campus computer lab access for students lacking personal devices
- Include AI data usage in institutional data provision programs
- Ensure AI platforms function on lower-end devices and older operating systems
- Provide offline-capable AI access for students with unreliable connectivity

Implementation: Technology access equity audits identifying student needs. Budget allocation for device loans, data provision, and platform development.

Policy 3: Protect Academic Integrity

Rationale: While not primary focus of this study, AI integration raises academic integrity concerns requiring proactive policy.

Specific Recommendations:

- Clearly communicate acceptable AI use boundaries (permitted support versus prohibited reliance)
- Design assessments resistant to AI shortcuts (authentic problems requiring procedural demonstration)

- Educate students on appropriate AI use and academic integrity principles
- Implement detection systems identifying unusual AI dependence patterns
- Establish clear consequences for academic integrity violations while supporting honest mistakes

Implementation: Update academic integrity policies explicitly addressing AI. Faculty professional development on integrity-preserving assessment design.

Policy 4: Allocate Resources for Faculty Development

Rationale: Effective AI integration requires faculty expertise in pedagogical design, technology use, and student support—expertise requiring development.

Specific Recommendations:

- Provide structured faculty professional development on AI pedagogy
- Allocate time in workload models for AI content development and monitoring
- Create faculty learning communities focused on AI integration challenges and solutions
- Fund pilot projects testing innovative AI applications with evaluation requirements
- Recognise AI integration excellence in promotion and tenure processes

Implementation: Faculty development programming aligned with AI adoption timelines. Workload adjustments recognising AI integration effort.

6.5.3 Curriculum and Assessment Redesign Imperatives

Industry Alignment Considerations

As Muller (2025) and Cudia et al. (2024) document, the Accounting profession increasingly relies on AI for routine tasks such as bookkeeping automation, predictive analytics, fraud detection, invoice processing, financial reporting, tax compliance. Professional Accounting firms (Deloitte, KPMG, PwC) extensively deploy AI-enabled technologies. This industry transformation necessitates curriculum evolution preparing graduates for AI-integrated workplaces.

Recommendations:

1. Integrate AI Literacy Across Curriculum:

- First-year: Basic AI concepts, responsible use, tool familiarity

- Second-year: AI applications in Accounting contexts (automated bookkeeping, data analytics)
- Third-year: Critical evaluation of AI outputs, professional judgment in AI contexts
- Fourth-year: Strategic AI use for complex problems, ethical considerations

2. Update Competency Frameworks:

- Traditional competencies (technical Accounting knowledge, procedural facility) remain essential
- Add emerging competencies (AI tool proficiency, data interpretation, human-AI collaboration, judgment in automated contexts)
- Align with SAICA competency framework while incorporating digital transformation realities

3. Redesign Assessments:

- Reduce focus on routine calculations increasingly AI-automated
- Increase emphasis on interpretation, judgment, communication, and professional scepticism
- Include AI-enabled assessments (students use AI tools appropriately during exams)
- Assess AI literacy and responsible use competencies explicitly

Work-Integrated Learning Integration

Recommendations:

1. Partner with Firms Using AI:

- Develop work-integrated learning placements exposing students to workplace AI use
- Invite practitioners to discuss AI's workplace role and required competencies
- Co-design curriculum with industry ensuring graduate preparedness

2. Provide Authentic AI Experiences:

- Use professional-grade Accounting software incorporating AI features
- Simulate realistic business scenarios requiring AI tool use
- Expose students to emerging technologies they'll encounter in practice

3. Bridge Academic-Professional Divide:

- Ensure academic AI use develops transferable competencies applicable in workplaces
- Avoid purely academic AI applications lacking professional relevance
- Evaluate curriculum-industry alignment regularly through advisory board input

6.5.4 Directions for Future Research

This study generates numerous questions warranting systematic investigation. While the findings illuminate first-year Accounting students' experiences with AI-generated resources, they simultaneously reveal significant gaps in understanding that future scholarship should address. Seven interconnected research directions emerge as particularly promising, each addressing distinct but complementary aspects of AI-enhanced learning in higher education.

The most critical gap pertains to objective learning outcome measurement. This study, like much existing AI-in-education research, measured students' perceptions of learning benefits through self-report instruments. However, perceived learning gains may not correspond to actual achievement measurable through validated assessments. Future research should employ experimental or quasi-experimental designs comparing AI users against carefully matched control groups on objective performance measures. Longitudinal tracking could examine whether first-year AI use predicts subsequent academic performance across multiple years, while cognitive assessments could measure specific competencies including conceptual understanding, procedural competence, and knowledge transfer ability.

Cross-institutional comparisons would illuminate whether effectiveness varies by implementation quality and institutional context. Methodologically, such research demands rigorous approaches including randomised controlled trials where feasible, propensity score matching when randomisation proves impractical, and difference-in-differences analyses capitalising on natural experiments. Without objective outcome data, effectiveness claims remain speculative; addressing this gap should constitute the field's highest research priority.

A second productive direction involves examining differential effectiveness across student subgroups. This study's relatively small qualitative sample hindered robust subgroup analyses, preventing a clear understanding of whether AI benefits some students substantially more than others. Large-sample quantitative studies could enable systematic comparisons across theoretically important dimensions. Do novice learners lacking prior

Accounting knowledge derive greater benefit than advanced learners with substantial background? How do learning preferences and cognitive styles moderate effectiveness? Does self-regulation capacity, the ability to maintain focus and manage learning autonomously, predict who thrives with AI support versus who struggles? Socioeconomic background and technology access likely shape experiences significantly; students with reliable high-speed internet and modern devices may engage differently than those dependent on limited mobile data and older phones.

Academic performance level represents another critical moderator. Do struggling students find AI provides essential scaffolding, or do high-achieving students leverage AI more effectively due to stronger foundational skills? Methodologically, such investigations require multi-level modeling Accounting for student nesting within courses and institutions, latent class analysis identifying distinct user profiles, and moderation analysis examining how individual characteristics shape the ease of use-usefulness-adoption pathway. Understanding differential effectiveness would enable targeted AI deployment maximising benefits for students most needing support while avoiding implementations that advantage already-privileged learners.

Longitudinal impact assessment constitutes a third vital direction. This study captured experiences during a single eight-week implementation period, revealing nothing about longer-term consequences. Multi-year tracking could examine whether first-year AI use influences retention rates, academic progression patterns, and graduation timelines, outcomes of particular concern in South African higher education where dropout rates remain problematically high. Skill development trajectories warrant investigation. Does early AI support accelerate students' movement toward autonomous learning by building confidence and foundational competence, or does it create dependency hindering self-directed learning development?

Professional outcomes represent an understudied but crucial dimension. Do AI-experienced graduates demonstrate superior workplace performance, adapt more readily to technology-intensive professional environments, or pursue different career paths than non-users? The technology's impact on SDL capacity development over time requires particular attention; does sustained AI use enhance self-management, self-monitoring, and intrinsic motivation, or does it undermine these capabilities by reducing the challenge necessary for their cultivation? Methodologically, cohort studies following students across multiple years, survival analysis modeling time-to-degree and dropout patterns, and

hierarchical linear modeling examining growth trajectories would provide appropriate analytical frameworks.

Enhanced AI design effectiveness represents a fourth critical direction with substantial practical implications. This study examined a relatively basic implementation, AI-generated text summaries and simple multiple-choice questions. Whether more sophisticated AI systems prove substantially more effective remains empirically unclear, yet investment decisions depend on answering this question. Comparative studies should evaluate effectiveness across sophistication dimensions. Do adaptive systems that adjust content difficulty based on student performance outperform static systems delivering identical content to all users? Does multimedia integration, combining text with diagrams, videos, animations, and interactive simulations, enhance learning compared to text-only delivery?

Should AI provide progressive difficulty that escalates challenge over time, and if so, what escalation rate proves optimal? How does automated grading compare to hybrid approaches incorporating human-in-the-loop review for complex responses? Design-based research could iteratively refine AI features through cycles of design, implementation, evaluation, and redesign, while controlled testing could isolate specific features' contributions to effectiveness. Methodologically, randomised comparisons, controlled experimentation, and systematic design variation would generate evidence informing cost-benefit calculations about AI sophistication investments.

Faculty perspectives and pedagogical practices represent a fifth important but underexplored direction. This study centered student experiences; how faculty understand, implement, and experience AI integration remains largely unexplored in South African contexts. A number of critical questions emerge. How do faculty actually integrate AI into existing teaching practices, as supplementary resource, primary content delivery mechanism, or assessment tool? What pedagogical strategies prove most effective for leveraging AI's affordances while mitigating its limitations? What challenges do faculty encounter during implementation, and how do institutional, technological, and pedagogical factors shape these challenges? Does AI integration affect faculty workload positively through reduced repetitive tasks, or negatively through increased complexity and student support demands? What professional development effectively supports faculty adoption, moving beyond technical training to address pedagogical integration and student support strategies?

Methodologically, in-depth interviews, ethnographic classroom observations, large-scale surveys, and communities of practice documentation would illuminate faculty experiences and identify effective implementation practices worthy of broader dissemination.

Cross-institutional and cross-disciplinary comparison constitutes a sixth necessary direction for establishing generalisability boundaries. This single-institution, single-discipline study cannot determine whether findings transfer across educational contexts. Multi-institutional studies examining diverse settings, well-resourced universities versus under-resourced institutions, urban campuses versus rural locations, research-intensive versus teaching-focused universities, would reveal how institutional characteristics shape AI effectiveness. Do resource-advantaged institutions achieve better outcomes through sophisticated implementations and robust support structures, or do resource-constrained institutions benefit more from AI's potential to partially compensate for limited faculty-student ratios?

Cross-disciplinary comparisons would determine whether findings specific to Accounting's procedural emphasis transfer to disciplines with different pedagogical requirements. Do conceptually-oriented humanities disciplines experience less theory-practice gap frustration since they lack Accounting's procedural demands? Do STEM fields requiring extensive problem-solving practice encounter similar limitations as Accounting? International comparisons would examine how educational system characteristics, cultural contexts, and technology infrastructure influence experiences. Methodologically, comparative case studies enabling deep contextual understanding, multi-site mixed-methods research generating both generalisable patterns and context-specific insights, and systematic reviews synthesising accumulating evidence would advance knowledge.

Finally, equity and access investigations demand urgent attention, particularly in South African contexts marked by profound digital divides and historical inequalities. This study identified concerning equity issues but lacked sampling breadth for thorough examination. How do variations in technology access, reliable internet connectivity, device quality, data availability, shape who benefits from AI resources and who encounters barriers? Language diversity represents another critical dimension; given AI's predominant English capability, how effectively do these tools serve multilingual learners whose home languages may not be English?

Disability access requires investigation. How well do current AI implementations accommodate diverse learning needs, including visual, auditory, cognitive, and mobility-related requirements? Most fundamentally, does AI integration narrow or widen

achievement gaps? If AI benefits already-advantaged students possessing strong self-regulation, prior knowledge, and technology access more than it supports disadvantaged students lacking these resources, implementation risks exacerbating rather than ameliorating educational inequality, an unconscionable outcome in equity-focused South African higher education. Methodologically, equity-focused mixed-methods research combining quantitative gap analysis with qualitative exploration of marginalised students' experiences, critical case studies examining equity explicitly, and participatory action research involving affected communities in investigation and solution design would generate needed evidence.

Given inevitable resource constraints, research priorities require strategic determination. Three directions warrant particular emphasis. First and most critically, objective learning outcome measurement must be prioritised. Without valid evidence that AI actually improves learning, not just that students perceive improvement, the entire enterprise rests on uncertain foundations. Even positive perceptions may reflect ineffective but comfortable learning experiences, while negative perceptions might accompany effective but challenging growth. Only objective assessment can resolve this uncertainty.

Second, enhanced AI design effectiveness investigations would inform whether substantial investments in sophisticated systems prove worthwhile compared to basic implementations. If carefully designed research reveals that simple, low-cost AI provides similar benefits to expensive, sophisticated systems, resource-constrained institutions could make informed decisions about appropriate investment levels. Conversely, if research demonstrates that sophistication substantially enhances effectiveness, the case for increased investment strengthens.

Third, equity investigations assume particular urgency in South African contexts where historical inequalities persist and educational transformation remains incomplete. AI implementation potentially advancing equity represents valuable innovation; AI exacerbating existing gaps would be ethically problematic and practically counterproductive. Understanding equity implications should guide implementation decisions, ensuring technology serves rather than subverts educational justice goals.

Collectively, these seven research directions would advance from the exploratory, perception-focused evidence base currently dominating AI-in-education scholarship toward more rigorous, outcome-focused, equity-conscious research generating actionable guidance for policy and practice. As AI capabilities evolve rapidly and adoption accelerates, the imperative for such evidence intensifies. Educational institutions cannot afford to make

high-stakes technology investments based primarily on enthusiasm, vendor claims, or isolated success stories. They require systematic, theoretically-grounded, methodologically rigorous research illuminating when, why, for whom, and under what conditions AI supports learning effectively and equitably. This study provides foundational understanding while simultaneously revealing how much remains unknown. The research agenda outlined here would substantially advance knowledge, informing evidence-based AI integration serving students, supporting faculty, and advancing educational mission in South African higher education and beyond.

6.6 Synthesis: Boundary Conditions and Generalisability

This section explicitly addresses study limitations and boundary conditions constraining generalisability, ensuring readers understand claims' appropriate scope.

Contextual Boundaries

Single Institution: Findings emerged from Emeritus College; transferability to other South African institutions remains uncertain. Emeritus's student demographics, resources, pedagogical culture, and technology infrastructure shape experiences in ways potentially unique to this context.

Single Semester: Eight-week implementation represents brief exposure; longer-term patterns may differ. Initial novelty effects may inflate early enthusiasm; conversely, benefits may emerge only with extended use.

Single Discipline: Accounting's particular characteristics, technical vocabulary, procedural emphasis, professional accreditation requirements may limit findings' applicability to other disciplines.

Specific AI Implementation: Findings reflect experiences with particular AI-generated summaries and simple questions; sophisticated AI implementations may generate different patterns.

Pietermaritzburg Campus Qualitative Sample: All interview and focus group participants attended one campus, potentially missing perspectives from larger urban campuses with different student profiles and resources.

Methodological Boundaries

Self-Report Data: Perceived benefits may not reflect actual learning gains; metacognitive inaccuracies mean students' self-assessments don't perfectly correspond to objective performance.

Non-Experimental Design: Without randomisation or control groups, causal claims remain tentative; observed effects might reflect selection bias (certain students chose to use AI extensively) rather than AI impact.

Retrospective Accounts: Qualitative participants reconstructed experiences from memory weeks after tool usage, potentially distorting or selectively remembering experiences.

Social Desirability: Students may have moderated criticisms given researcher's institutional affiliation and Campus Head role.

Generalisability Claims

Given these boundaries, appropriate generalisability claims include:

What can be claimed:

- Patterns observed at Emeritus College likely operate at similar institutions (under-resourced South African universities with diverse student populations)
- Theoretical insights (TAM extensions, SDL refinements, conditional effectiveness framework) likely transfer beyond immediate context, though requiring empirical validation
- Design principles grounded in cognitive and pedagogical theory (scaffolding, alignment, multimodal support) should apply broadly, though implementation specifics vary contextually

What cannot be claimed:

- Findings don't necessarily transfer to affluent, well-resourced institutions with different student profiles
- Results may not generalise to other disciplines with different pedagogical requirements and assessment structures
- Effectiveness observed (or not observed) with basic AI doesn't predict outcomes with sophisticated AI systems
- Perceptions measured may not reflect actual learning outcomes assessable through objective measurement

Readers applying findings to their contexts should consider:

- How similar is their context to Emeritus College regarding student characteristics, resources, pedagogical culture?

- How comparable is their AI implementation to the Generative AI tool studied?
- How aligned are their discipline's characteristics with Accounting's procedural emphasis?
- Do they have resources to address identified limitations (e.g., developing sophisticated rather than basic AI)?

This transparency about scope enables appropriate evidence use while acknowledging uncertainty.

6.7 Conclusion

This chapter interpreted findings from a mixed-methods case study examining first-year Accounting students' experiences with customised Generative AI resources. Through integration of SDL theory and TAM, the analysis revealed that AI effectiveness proved highly conditional, depending on learning stage, task type, learner characteristics, and integration strategy. AI effectively supported foundational conceptual understanding, particularly benefiting novice learners requiring accessible explanations and confidence-building. However, pedagogical misalignment between theory-focused AI content and practice-focused assessments, coupled with inadequate support for procedural competence and higher-order thinking, fundamentally limited educational effectiveness.

The theory-practice gap emerged as the most consequential limitation. While AI clarified concepts and outlined procedures, it provided insufficient practice opportunities for developing fluent procedural execution, the cornerstone of Accounting competence. This gap reflects a fundamental tension. AI excels at information transmission but struggles with competency development requiring extensive, varied, progressively challenging practice with sophisticated feedback. Students recognised this limitation, explaining moderate overall perceptions and strategic resource choices favouring traditional materials for exam preparation despite valuing AI for initial concept introduction.

Usability significantly mediated effectiveness, functioning as pedagogical gatekeeper. The strong ease of use-perceived usefulness correlation reflected mechanism whereby usability barriers prevented sustained engagement necessary for experiencing content benefits, not merely statistical association. Mobile-only access, interface limitations, and functional constraints created friction that caused premature disengagement even when content quality was high. This finding elevates usability from user experience concern to educational priority, pedagogically excellent content proves useless if students cannot or will not access it.

Students' instrumental orientation toward assessment preparation represented rational response to professional education's credentialing emphasis rather than learning deficiency. However, instrumental and intrinsic motivations coexisted, students valued both exam success and genuine understanding, recognising that assessment requiring deep comprehension makes intrinsic learning instrumentally valuable. This coexistence challenges scholarship positioning these motivation types as opposing and suggests pedagogy should leverage rather than resist instrumental goals through constructive alignment ensuring mastery becomes strategically advantageous.

Theoretical contributions include extending TAM by disaggregating PU by knowledge type, positioning EOU as a pedagogical gatekeeper, and centering task-technology fit as critical mediator. SDL theory refinements include proposing context-appropriate SDL expectations recognising differences between adult education and professional education contexts, developing scaffolded SDL framework emphasising developmental progression, and acknowledging motivation spectrum blending instrumental and intrinsic elements. The integrated conditional effectiveness framework synthesises technology, pedagogical, learner, and context factors predicting when AI supports learning effectively.

Practical implications emphasise design principles for AI pedagogy, scaffolding from foundational to advanced, systematically integrating theory and practice, explicitly aligning with assessments, accommodating diverse learning needs, enabling accurate self-monitoring, and maintaining human-in-the-loop support. Institutional policy recommendations address quality assurance, equitable access, academic integrity, and faculty development. Curriculum implications highlight industry alignment needs as the Accounting profession transforms through AI adoption, requiring graduates prepared for AI-integrated workplaces.

This study contributes empirical evidence to emerging scholarship on AI in South African higher education, demonstrating both potential and limitations. AI provides valuable foundational learning support, particularly in resource-constrained contexts where students face conceptual barriers and large classes limit personalised attention. However, current implementations insufficiently support comprehensive professional competence development, functioning as supplementary resource rather than transformative pedagogical tool. Realising AI's full potential requires addressing identified limitations through sophisticated system development, intentional pedagogical integration, faculty support, and continuous evaluation.

The conditional effectiveness pattern revealed that AI helps some students, with certain learning tasks, at particular developmental stages, when integrated strategically, challenges simple adoption or rejection decisions. Rather than asking whether to use AI, institutions should ask for which students, purposes, and contexts does AI provide value, and how can we design implementation maximising benefits while mitigating limitations? This nuanced approach, grounded in empirical evidence and theoretical understanding, enables responsible, effective AI integration serving educational mission rather than uncritical technology adoption.

As South African higher education navigates fourth industrial revolution imperatives while addressing persistent equity challenges and resource constraints, AI offers potential pathways for expanding access, enhancing quality, and preparing graduates for transformed workplaces. However, potential realisation requires thoughtful implementation informed by evidence, guided by pedagogical principles, supported by institutional commitment, and continuously evaluated for effectiveness and equity. This study provides foundational understanding supporting such informed implementation while identifying critical questions warranting further investigation.

Chapter 7 concludes the dissertation by synthesising overall contributions, reflecting on the research journey, and offering final thoughts on AI's evolving role in transforming South African Accounting education within the broader higher education landscape.

Chapter 7: Key findings of Generative AI in first-year Accounting learning

7.1 Introduction

Chapter 6 presented an interpretation and discussion of the primary findings from the study, situating the findings within the theoretical framework and empirical literature. The theoretical extensions afforded the creation of an integrated AI-Enhanced Learning (ICEFL) framework. This chapter concludes the dissertation by summarising the major findings in relation to the specific research questions, as well as the theoretical, methodological and practical contributions of the study building upon the ICEFL framework for practice and policy. The chapter concludes with recommendations for future research and a final reflection on the research journey.

I explored responses to the critical research questions using a mixed-methods research approach, which situated the study within the pragmatic paradigm. This enabled a contextual understanding of how a Generative AI tool shaped students' learning within a first-year Accounting module, enabling an understanding of not just what their experiences were but why certain features supported learning whilst others created barriers. The summary of the major findings in this chapter presents the conditions under which AI proved beneficial and what individual, pedagogical and technological factors mediated effectiveness.

7.2 Summary of major findings

7.2.1 Foundational learning

The first major finding pertained to the effectiveness of the Generative AI tool to support foundational learning and conceptual understanding (fully established in Section 6.2.1).

This finding relates to research question 2; how did AI shape learning outcomes and skill development in the ACC1A module. It is understood that the AI-generated summaries reduced the cognitive burden on students by supporting them with readily available concept summaries for ease of comprehension and understanding. This was particularly useful for students who were not exposed to Accounting at school and were being exposed to Accounting terminology for the first time.

The ability of Generative AI to act as a cognitive scaffold reveals the scholarly significance of this finding and contributes to literature related to technology enhanced learning.

7.2.2 Theory-Practice Gap

The second major finding related to the gap between procedural and declarative knowledge development, as established in Section 6.2.2.

This finding also responds to research question 2 by revealing how the AI-generated resources outlined the steps but offered insufficient practice for fluency. The AI tool's pedagogical limitation to develop procedural knowledge moderated PU because conceptual support inadequately addressed students' primary need to pass their assessments which required procedural competency. Students' acknowledgement of this limitation demonstrated students' self-monitoring.

The significance of this finding underscores that designing AI tools for content transmission alone hinders AI's transformational potential within higher education contexts.

7.2.3 Conditional effectiveness for learning

The third major finding related to the conditional effectiveness of the AI tool (well established in chapters 4 and 5). This finding relates to research question 3, illuminating the conditions under which students experienced benefits and challenges.

Conditional effectiveness represents the study's most significant finding, advocating for AI to be designed to enable adaptive ability that can support diverse learning trajectories, diverse cognitive needs (declarative to procedural), diversity in learning preference and be effectively positioned within broader learning ecosystems.

7.2.4 Usability as a gateway to pedagogical perceived usefulness

The fourth finding revealed that insufficient EOU results in non-use, eliminating opportunity for usefulness evaluation and provides a response to research question 2 (established in Section 6.2.3).

Students identified limitations of the AI tool when comparing it to other commercially available AI tools, demonstrating that students entering higher education most likely have prior AI exposure (Moore & Lookadoo, 2024).

This critical finding expresses that user experience design has to extend beyond aesthetic considerations to the prioritisation of interface design, user testing, and continuous usability refinement. Without such prioritisation and investment, AI's pedagogical potential remains limited irrespective of the quality of educational content.

7.2.5 Intrinsic and instrumental motivations coexist

The fifth major finding related to the understanding that students were motivated by both the instrumental and intrinsic value of the Generative AI tool.

This finding relates to research question 1, demonstrating that students valued the AI tool for exam preparation and intrinsic motivation to drive SDL. Whilst some authors position instrumental and intrinsic motivation types as opposing, this study suggests that in

professional education, assessment requiring deep comprehension makes intrinsic learning instrumentally valuable.

Most relevant to scholarship is the understanding that instrumental and intrinsic motivation can co-exist. It is therefore recommended that AI integration into pedagogical design for Accounting can productively leverage instrumental motivation through constructive alignment.

This section underscored the five major findings across the quantitative and qualitative phases of the study, as well its relevance within contemporary higher education. This relevance is further discussed and summarised by extrapolating the explicit implications at multiple levels of influence.

7.3 Implications of Findings

The implications of the study's findings are summarised across four levels; namely the individual level, pedagogical level, institutional level and the theoretical level.

7.3.1 Individual level

At the individual level, findings illuminate factors mediating AI effectiveness for diverse learners in professional education contexts. The implications of the findings which revealed that the AI tool was inadequate to cater to the diversity of students' individual characteristics and learning needs suggests specific design implications. The first pertains to the need for the AI-generated resources to be available across multiple platforms. To cater to students' preferences, access should be available via whichever platform suits their current context (ie. mobile/laptop, etc). The second pertains to the need for AI intuitiveness. Students evaluated the usefulness of the AI tool against commercially available AI tools that enable ease of search functionality and navigation, along with real-time responses. Educational AI needs to meet these standards to be perceived as easy to use and useful or risk being perceived as inferior, as was the outcome in this case study. Thirdly, the findings imply that AI interactivity is critical. Static content delivery represents minimal AI capability. Advanced AI should support dialogic interaction, enabling students to ask questions, AI provided explanations, student request clarification, AI aligned explanations to student understanding level. This conversational learning aligns with socio-constructivist pedagogy (Vygotsky, 1978) and leverages AI's interactive potential rather than merely using it as text generator. Finally, AI tools integrated with existing learning management systems and productivity tools enable a seamless learning experience. Students shouldn't need to be overwhelmed by multiple, disconnected platforms. AI should embed within LMS environments where students already work, with exports to note-taking applications,

connections to digital textbooks, and links to assessment platforms. At the individual level, the implications of the findings reveal that AI effectiveness is dependent on strategic design decisions related to platform accessibility, intuitive design, interactive functionality and seamless integration into existing student learning infrastructure. Addressing these factors that mediate AI effectiveness will ensure that diverse learner characteristics and needs are met.

7.3.2 Pedagogical level

At the pedagogical level, the finding that AI's static nature resulted in declined usefulness has implications for AI design that supports procedural and comprehensive learning acquisition rather than only foundational knowledge acquisition. The first implication pertains to the need for AI to provide extensive practice opportunities. This requires moving beyond text generation to incorporate Accounting simulations and problem-based learning opportunities. The second implication pertains to the need for AI to be adaptable to afford scaffolding opportunities to align to students' competence progression, transitioning from declarative knowledge acquisition to procedural and comprehensive knowledge acquisition. The third implication pertains to the need for AI-generated resources to directly support assessment outcomes. The fundamental misalignment between the recall and comprehension type pathway questions in comparison to the calculation and application-type assessment questions resulted in student disengagement. To address this, AI resources must develop competencies that assessments seek to measure. Finally, findings pertaining to marking errors of responses to pathway questions and lack of lecturer oversight has implications for design that prioritises a human-in-the-loop approach (Zanzotto, 2019). This will enable lecturers to monitor student performance and intervene with suitable support interventions to address learning gaps. At the pedagogical level findings imply that AI should augment existing pedagogy, not replace existing pedagogical mechanisms.

7.3.3 Institutional level

At the institutional level, findings related to the theory-practice gap have policy considerations for equitable, effective AI integration relevant for the SAHE context. Whilst it is understood that institutions of higher learning in South Africa face funding challenges, it remains important that AI is strategically implemented. Policy-makers need to assess the substantive learning impact of AI tools to avoid adopting solutions that offer the semblance, but not the reality, of enhanced student competencies. The second implication of the theory-practice gap pertains to the need for institutions to design AI to meet both conceptual mastery and practical application that aligns with pedagogical and professional

accreditation requirements (such as SAICA for Accounting modules). Finally, the theory-practice gap has implications for the equitable integration of AI such that all students are given a fair opportunity to develop procedural competence, whether as part of work-integrated learning opportunities or additional academic opportunities that extend beyond the curriculum. At the institutional level, the theory-practice gap presents design opportunities to ensure the equitable delivery of AI-mediated learning support.

7.3.4 Theoretical extensions

Contribution of the ICEFL Framework

The Conditional Effectiveness Framework for AI-Enhanced Learning (ICEFL) underscores the conditions necessary for effective learning and the factors that create barriers (Section 6.4.4). It aims to guide AI design decisions, and explicitly highlights usability and pedagogical alignment as the enablers that should be prioritised. The multi-factor metrics incorporated into the framework can be used by instructional designers to evaluate whether AI meets conditional effectiveness criteria. Unlike generic AI adoption models, ICEFL explicitly prescribes when AI integration will derive the most benefit based on interactions between technological, pedagogical, student and contextual factors (student cohorts, module types, learning stage and supplementary support).

Contribution of ETAM-E

The ETAM-E framework, established in Section 6.4.1, disaggregates PU by knowledge type, positions EOU as a pedagogical gatekeeper and task-technology fit as a central mediator.

This framework is especially valuable for institutions of higher learning and researchers alike. It enables a more precise understanding of when and why AI integrated tools prove more or less effective. Utilised as a diagnostic tool, it can support instructional designers to detect and address usability bottlenecks. Moreover, it will support in aligning AI technologies to task requirements to mediate EOU, PU and adoption. This extension of TAM ultimately underscores the need for institutions to consider learning task structures, assessment demands and performance criteria to effectively integrate AI into teaching and learning.

Contribution of redefined SDL

The proposed scaffolded SDL framework posits that AI resources should align with students' organic progression of SDL readiness and competence and educational context.

The framework contributes to the current discourse of AI integration by advocating for technology-enhanced SDL through intentional design decisions and strategies. It is therefore valuable for instructional designers by demonstrating how AI technologies can be leveraged to enhance students' development of SDL.

7.4 Recommendations for higher education practice and policy

7.4.1 Accounting education

The findings of the study and theoretical extensions derive specific recommendations for Accounting education:

- The integration of AI literacy across the curriculum from first year to third year, addressing specific learning needs and outcomes at each level of study
- Update competency frameworks to develop traditional and emerging competencies, whilst aligning to course accreditation requirements and integration of digital affordances
- Redesign assessments to refocus from routine calculations that are becoming increasingly AI-automated to assess contemporary competencies that align with industry needs.
- Build AI literacy, whilst making explicit the need to use AI responsibly
- Prioritise industry partnerships to provide authentic experiences for students to build Accounting graduate attributes

In summary, the recommendations for Accounting education focus on nuances within the SAHE context, and underscores the need for locally grounded policy and practice rather than uncritical transfer of international models. The sections to follow make these recommendations explicit.

7.4.2 Recommendations for pedagogical design

The study provides explicit recommendations for pedagogical design:

- AI should be designed to support the scaffolding of learning progress as students' competence progresses during the course of a semester. This will enable students to transition from declarative knowledge acquisition to procedural knowledge acquisition through the mastery of foundational concepts to complex, authentic applications.
- Strategic AI integration requires theory and practice to be implemented systematically, affording both theoretical and practical exposure to each concept. Well-scaffolded practice will address any theory–practice gaps.
- AI resources must align to module and assessment outcomes.

- Diverse learning needs can be accommodated through multimodal content, flexible platforms, and accessibility features.
- Sophisticated feedback, diagnostics, and learning analytics will support accurate self-monitoring
- Design specifications for human-in-the loop support should integrate faculty oversight and learning analytics to provide targeted pedagogical intervention.

7.4.3 Recommendations for policy

Recommendations are drawn from the study's findings availing four key policy propositions:

- Integrate quality assurance mechanisms into existing course approval, requiring AI alignment documentation in course outlines
- Conduct technology access equity audits identifying student needs. Allocate budget for device loans, data provision, and platform development.
- Update academic integrity policies explicitly addressing AI and develop faculty's professional competence to preserve academic integrity
- Develop faculty's AI expertise

Overall, these recommendations support effective AI integration. Stringent quality assurance and strategic alignment will enhance pedagogical value whilst ensuring equitable delivery of teaching and learning. Policies serve to protect academic integrity whilst strengthening faculty's competence to effectively incorporate AI into practice.

7.5 Recommendations for future research

The study presents seven research directions that serve to advance exploratory, perception-focused research that currently dominates AI-in-education scholarship toward more rigorous empirical findings. This transition in research focus is critical for outcome-focused research that will provide more accurate and specific guidance for policy and practice. The following explicit recommendations are made:

- Employ experimental or quasi-experimental designs comparing AI users against carefully matched control groups on objective performance measures. Longitudinal tracking could examine whether first-year AI use predicts subsequent academic performance across multiple years, while cognitive assessments could measure specific competencies including conceptual understanding, procedural competence, and knowledge transfer ability. Cross-institutional comparisons would illuminate whether effectiveness varies by implementation quality and institutional context. This will require specific methodological approaches such as randomised controlled trials,

propensity score matching when randomisation proves impractical, and difference-in-differences analyses capitalising on natural experiments. Without objective outcome data, effectiveness claims remain speculative; addressing this gap should constitute the field's highest research priority.

- Examine differential effectiveness across student subgroups. This study's relatively small qualitative sample hindered robust subgroup analyses, preventing a clear understanding of whether AI benefits some students substantially more than others. Large-sample quantitative studies could enable systematic comparisons across theoretically important dimensions, such as whether novice learners lacking prior Accounting knowledge derive greater benefit than advanced learners with substantial background. Similarly, examining further individual mediating factors, such as learning preferences, cognitive styles, self-regulation, socioeconomic background, technology access, and academic performance would elicit more rigorous findings that will enable targeted and equitable deployment
- Employ longitudinal impact assessment to reveal longer-term consequences. Multi-year tracking could examine whether first-year AI use influences retention rates, academic progression patterns, and graduation timelines, outcomes of particular concern in South African higher education where dropout rates remain problematically high. Similarly, skill development trajectories warrant extended research to evaluate specific conditional factors, such as whether AI-experienced graduates demonstrate superior workplace performance or adapt more readily to technology-intensive professional environments. Methodologically, cohort studies following students across multiple years, survival analysis modeling time-to-degree and dropout patterns, and hierarchical linear modeling examining growth trajectories would provide appropriate analytical frameworks to identify AI's impact on SDL development over time including self-management, self-monitoring and intrinsic motivation.
- Whether more sophisticated AI systems prove substantially more effective remains empirically unclear as this study focused on a basic implementation. Employing comparative studies should evaluate effectiveness across more sophisticated AI tools that offer adaptation establishing whether aggregated difficulty aligns more effectively to students' diverse levels of competence. Moreover, design-based research could iteratively refine AI features through cycles of design, implementation, evaluation, and redesign, while controlled testing could isolate specific features' contributions to effectiveness. Methodologically, randomised comparisons, controlled experimentation,

and systematic design variation would generate evidence informing cost-benefit calculations about AI sophistication investments.

- Faculty experiences and pedagogical practices regarding AI integration in South African higher education remain largely unexplored. Key questions include how faculty implement AI, which strategies effectively leverage its benefits, the challenges encountered, impacts on workload, and the professional development needed for effective adoption. Research using interviews, observations, surveys, and communities of practice could illuminate these experiences and identify best practices for broader dissemination.
- Employ a cross-institutional or cross-disciplinary research to assess whether findings generalise beyond a single institution and discipline, as was the case in this study. A comparison across multiple tertiary institutions, assessing convergence and divergence with international literature will reveal how institutional resources, pedagogical requirements, and technology infrastructure influence AI effectiveness. Methodologies such as comparative case studies, multi-site mixed-methods research, and systematic reviews would generate both generalisable insights and context-specific understanding
- Finally researching equity and access in AI integration is a vital study within the SAHE context owing to the country's history that manifests as diverse student needs. Specific concerns that require further interrogation include disparities in technology access, language and disability barriers and whether AI reduces or increases student academic progression. Mixed methods research and case study methodological approaches will prove valuable for such research studies

In conclusion, the recommendations for future research centres around three research focus areas which include the explicit measurement of learning outcomes, examination of specific mediating factors that influence effective AI design and equity investigations within the SAHE context. With the ongoing integration of AI in higher education, systematically rigorous methodological approaches are imperative to ensure that empirical findings provide evidence-based outcomes to guide institutions with the effective integration of AI into practice.

7.6 A personal reflection of the research journey

My research journey commenced at the start of 2025. As a novice researcher I was apprehensive about embarking upon a mixed-methods study, but accepted the expert guidance of my super, Supervisor. The feedback from the panel at my oral review confirmed this decision as one which was critical to establishing rigour for my study. Data collection for the quantitative phase began in July through an online questionnaire

administered to 416 students. Responses were received from 149 student participants. The quantitative findings identified significant relationships and patterns, illuminating that 45.6% of students felt neutral about their engagement with the customised Generative AI tool. Insights were also gleaned regarding students' instrumental orientations and established findings that indicated that usability predicted benefits. 48-58% of students perceived AI-generated resources as useful for assessment preparation and conceptual understanding. 40-47% of students provided neutral responses across multiple constructs suggesting conditional or context-dependent experiences. Strong positive correlations between EOU and PU indicated that usability significantly influenced learning benefits. Quantitative findings also revealed that students valued AI resources for instrumental goals. This addressed the first research question; "What are first year students' learning experiences of engaging with AI-generated lecture summaries and pathway questions in the ACC1A module?" However, statistical tests could not reveal how and why patterns emerged and why students' perceptions divided into thirds (agree/neutral/disagree). These limitations of the quantitative phase further affirmed the decision for the methodological approach of a mixed-methods design. Qualitative findings were necessary to provide a rich understanding of individual student experiences that informed the patterns established through the quantitative phase.

The qualitative phase addressed the interpretive gaps left by the quantitative analysis. Through semi-structured interviews with 14 students and focus group discussions with 10 students at the Pietermaritzburg campus, findings revealed how students used the AI tool and what outcomes were achieved, along with insights into why certain features supported learning whilst others created barriers, and finally insights were established into what conditions AI proved beneficial and mediated effectiveness. Addressing research question 2 "How did AI shape learning outcomes and skill development," qualitative findings presented 4 key outcomes. Firstly, AI effectively supported foundational declarative knowledge acquisition, providing accessible explanations of Accounting concepts and terminology. Secondly, AI provided limited procedural knowledge development, outlining steps but offering insufficient practice for fluency. Thirdly, AI supported lower-order cognitive skills (remembering, understanding, basic application) while neglecting higher-order skills (analysis, evaluation, creation). Fourthly, the theory-practice imbalance meant students developed conceptual understanding but inadequate practical competency for assessment success. Addressing research question 3 "why did students perceive benefits or challenges," qualitative findings identified key outcomes as to when benefits and challenges were experienced. Benefits occurred when AI was used for initial topic

introduction and conceptual overview (advance organiser function), students strategically integrated AI with other resources instead of exclusive reliance, when novice learners needed confidence-building through accessible explanations and when students valued flexible, mobile access for fragmented study time. Challenges occurred when pedagogical misalignment was experienced between AI content (theory-focused) and assessment demands (practice-focused) created usefulness deficits, usability barriers (mobile-only access, poor interface, limited functionality) prevented sustained engagement, when insufficient accommodation of learning diversity (visual/auditory needs unmet, lack of interactivity) alienated certain learner types and when limited AI responsiveness (inaccurate grading, inability to explain reasoning, non-adaptive content) required human-in-the-loop support.

7.7 Conclusion

Chapter 7 concludes this dissertation through a synthesis of the study's contribution to existing scholarship on AI integration in higher education, including a reflection of my personal research journey, and affording concluding remarks on AI's potential, through thoughtful implementation, to expand access, enhance quality and prepare graduates for transformed workplaces. The study provided a comprehensive exploration of the integration of a customised Generative AI tool within a first-year Accounting module within a PHEI in South Africa. Quantitative and qualitative findings elucidated both opportunities and limitations. Empirical evidence highlighted the theory-practice gap as the most consequential limitation, which manifested itself through three dimensions. The study contributes empirically to the discourse on Generative AI's integration within South African higher education, specifically addressing a significant gap in scholarship on student experiences with AI-integrated learning in Accounting education. While international literature documents AI adoption in various educational contexts, limited research examines AI effectiveness in South African higher education institutions, particularly in foundational Accounting courses where students face substantial conceptual challenges. The study's significance lies in its systematic investigation of both benefits and limitations through mixed-methods inquiry, moving beyond enthusiasm or scepticism toward evidence-based understanding of AI's conditional effectiveness in professional education contexts. The study's findings are timely, given universities task to take strategic decisions about AI integration requiring evidence-based guidance balancing potential benefits against implementation challenges. In conclusion, the study underscores that simplistic narratives positioning AI as either a silver bullet or existential threat prove unhelpful;

advocating for a more nuanced understanding of conditional effectiveness under varying circumstances which provides a more useful foundation for decision-making.

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Appendix 1: Ethical Clearance Certificate



24 July 2025

Evendree Reddy (201505722)
School of Education
Edgewood Campus

Dear E Reddy,

Protocol reference number: HSSREC/00009041/2025

Project title: Exploring the use of customised Generative Artificial Intelligence in first-year Accounting learning: A case study of a private higher education Institution

Degree: Masters

Approval Notification – Expedited Application

This letter serves to notify you that your application received on 21 July 2025 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**.

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.

Incidents of adverse events and serious adverse events (AEs and SAEs) should be reported in writing to HSSREC, the study sponsors, and any regulatory authority (where appropriate), within 7 working days of the occurrence for local sites and 14 days for all other South African sites.

This approval is valid until 24 July 2026.

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.

HSSREC is registered with the South African National Health Research Ethics Council (REC-040414-040).

Yours sincerely,

Doctor Shamila Naidoo (Interim Chair)

/nng

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 2: Gatekeeper's Letter





**THE INDEPENDENT
INSTITUTE OF
EDUCATION**



Reference: R.16016 [RPGS04]
Enquiries: research@iie.ac.za



04 July 2025



Letter of Institutional Consent

Initials and surname:	Evendree Reddy
Institution Registered at:	UKZN
Qualification:	Master of Education in Higher Education
Title of study/paper:	Exploring Customised Generative AI in First Year Accounting Learning: A Case Study of a Private Higher Education Institution (PHEI).



Dear Evendree,

We are pleased to inform you that the IIE Ethics Committee has reviewed and provided consent to conduct your research project entitled: "Exploring Customised Generative AI in First Year Accounting Learning: A Case Study of a Private Higher Education Institution (PHEI)."



The following conditions are the standard requirements attached to the approval of all applications to conduct research involving human participants:

- Approval will be for a period of two (2) years, starting from the date of approval.
- You should notify the IIE Research Ethics Committee (REC) regarding any alteration to the approved project.
- You should notify the IIE REC in the event of any adverse effects on participants or of any unforeseen development that might compromise the ethical integrity of your research project.
- The researcher(s) will need to obtain informed consent in writing from the participants/ respondents in their sample if the study is not anonymous.
- A copy of this letter must be forwarded to the relevant person(s) at the campus/es that would be involved in this research study.
- You are permitted to collect data only on campuses you have selected in your application form (Annexure G (b)).
- Research must be conducted in such a way that the normal programme and operations of the campus / office is not interrupted.
- A report and a copy of any published outputs should be submitted to the IIE REC upon the completion of the project.
- You are required to uphold the IIE's Ethics stance as described in the Research and Postgraduate Studies Policy (IIE007). The policy is available on the institutional website.

On behalf of The IIE Ethics Committee



Dr Reza Hosseini
Acting Dean: Research and Postgraduate Studies
The Independent Institute of Education



ADvTECH House: Inanda Greens, 54 Wierda Rd West, Wierda Valley 2196
P.O. Box 2369, Randburg 2125
Directors: GD Whyte (UK), JDR Oesch, MD Aitken, SCD Lurie
Group Company Secretary: CB Crouse



The Independent Institute of Education (Pty) Ltd is registered with the Department of Higher Education and Training as a private education institution under the Higher Education Act, 1997 (reg. no. 2007/HE07/002).
Company registration number: 1987/004754/07.

Appendix 3: Informed Consent

INFORMED CONSENT

Information Sheet and Consent to Participate in Research

3 September 2025

Dear prospective participant

My name is Evendree Reddy, a registered student at UKZN pursuing a Master of Education in Higher Education (Student Number: 201505722). The title of my research is: **Exploring the Use of Customised Generative AI in First-Year Accounting Learning: A Case Study of a Private Higher Education Institution (PHEI).**

You are being invited to participate in a study that involves research which aims to understand how the use of lecture summaries and homework questions on MathU have shaped your learning experience in the ACBP5121 module. May I formally invite you to participate in this study in the form of an interview (Pietermaritzburg campus only) and focus groups (Pietermaritzburg campus only).

This study has been ethically reviewed and approved by the UKZN Humanities and Social Sciences Research Ethics Committee (approval number HSSREC/0009041/2025).

In the event of any problems or concerns/ questions you may contact the researcher at [REDACTED] the UKZN Humanities & Social Sciences Research Ethics Committee, contact details as follows:

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

I would like to emphasise that information that you provide will be used for scholarly research only. Your participation is entirely voluntary; you have a choice to participate, not to participate or stop participating

in the research. You will not be penalised for taking such an action. Your views in this interview will be presented anonymously; your name will not be disclosed in any form in the study. The interview and focus group sessions will take approximately 30 minutes long, respectively, and the record as well as other items associated with the interview will be held in a password-protected file accessible only to myself and my supervisor(s). After a period of 5 years, in line with the rules of the University of KwaZulu-Natal, recordings and notes will be disposed of by shredding and destruction.

If you agree to participate, please sign the declaration attached to this statement

CONSENT

I _____ have been informed about the study entitled **Exploring the Use of Customised Generative AI in First-Year Accounting Learning: A Case Study of a Private Higher Education Institution (PHEI)** by Evendree Reddy.

I hereby confirm that:

- I understand the purpose and procedures of the study, which includes an interview and focus groups.
- I have been given an opportunity to ask 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.
- If I have any further questions/concerns or queries related to the study, I understand that I may contact the researcher _____

- 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 the researcher using the aforementioned contact information.

Additional consent

I hereby provide consent to:

Audio-record my interview / focus group discussion	YES/ NO
--	---------

Signature of Participant

Date

Signature of Witness
(Where applicable)

Date

Appendix 4: Quantitative Questionnaire

Instrument 1: Cross-sectional questionnaire assessing overall student experience, including perceived benefits and challenges

Title: Online Cross-sectional Questionnaire – Overall perceptions of student learning experience

Section 1: Demographic Information

1. **Age:** _____
2. **Gender:**
 - ☐ Male
 - ☐ Female
 - ☐ Non-binary
 - ☐ Prefer not to answer
3. **Have you used AI tools before?**
 - ☐ Yes
 - ☐ No
 - ☐ Not Sure

Section 2: Likert Scale Questions

Instructions: Please indicate how much you agree or disagree with the following statements.

Statement	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1. The AI-generated lecture summaries helped me understand the key concepts of the ACC1A module.	1	2	3	4	5
2. The AI-generated lecture summaries were easy to understand and follow.	1	2	3	4	5
3. The AI-generated homework questions helped me reinforce my learning and improve my understanding of the material.	1	2	3	4	5
4. The AI-generated homework questions were useful in preparing	1	2	3	4	5

Statement	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
me for exams and assessments.					
5. I felt confident in using the MathU platform to assist with my learning in the ACC1A module.	1	2	3	4	5
6. The AI-generated resources (summaries and homework questions) made learning more engaging for me.	1	2	3	4	5
7. I faced technical difficulties or challenges while interacting with the AI-generated resources.	1	2	3	4	5
8. The use of AI-generated resources in the ACC1A module improved my overall learning experience.	1	2	3	4	5
9. I would prefer to have more AI-generated resources integrated into the learning materials for the ACC1A module.	1	2	3	4	5
10. AI-generated resources are a useful supplement to traditional learning materials in the ACC1A module.	1	2	3	4	5

Section 3: Open-Ended Questions

Instructions: Please answer the following questions to provide more detailed insights into your learning experience.

- Can you describe your overall experience with the AI-generated lecture summaries in the ACC1A module?**
(Please provide as much detail as possible.)
- How did the AI-generated homework questions impact your understanding of the module content?**
(Consider whether these questions helped you retain or apply knowledge more effectively.)

3. **Were there any challenges you faced while using the AI-generated tools for your learning?**
(Please elaborate on any difficulties or barriers you encountered.)
4. **In what ways do you think AI-generated resources could be improved to better support your learning in the ACC1A module?**
(Feel free to suggest any features or changes you believe could enhance the experience.)
5. **How did the AI tools influence your motivation and engagement with the ACC1A module?**
(Please explain whether the use of AI tools increased your interest or participation in the course.)
6. **Do you think the integration of AI tools in your learning will have a long-term impact on your academic success in the ACC1A module? Why or why not?**
(Please explain your thoughts.)
7. **In what other ways could AI tools support your learning in the future, both in ACC1A and other modules?**
(Consider other potential applications or benefits of AI tools for your studies.)

Appendix 5: Semi-structured Interview

Instrument 2: Semi-structured interview assessing how the customised Gen. AI tool shape first-year students' understanding of learning outcomes and skill development in the ACC1A module?

Title: Semi-structured interview – Experience related to comprehension of learning outcomes and skill development

1. Please explain how the AI generated lecture summaries supported you to understand what the key learning outcomes of ACC1A were?
2. Please describe the way in which the homework questions may have helped you to think more deeply about accounting terms you were taught in class?
3. Please describe if the AI generated summaries and homework questions merely supported your understanding of concepts or did it also help you to apply and analyse concepts taught in the module? Please explain
4. In what ways were engaging with the AI generated summaries different from engaging with your textbook and module guide to support your learning?
5. How did the relevance of the summaries and homework questions in relation to what was taught in class influence your learning?
6. Please describe your experience of completing the homework questions
7. In what ways did the AI tool influence your development of skills such as critical thinking or problem-solving?
8. How did the AI tool influence your overall academic performance?

Appendix 6: Focus Group Schedule

Instrument 3: Focus Group Activities

To promote reflection, discussion, and interaction among the participants about how the Gen AI tool influenced their conceptual understanding, application of knowledge, and skills development (e.g., critical thinking, self-directed learning, problem-solving). The activities align with the constructivist approach guiding this part of the study (Research Question 2 – How does a customised Generative AI tool shape 1st year students' understanding of learning outcomes and skill development in ACC1A?).

Activity 1: Concept Mapping – "From Summary to Skill"

Objective: In this activity, my intention is to explore how participants connected AI-generated lecture summaries to their understanding of learning outcomes for ACC1A. For this reflection activity we are going to draw on learning units 3 and 4 that focussed on VAT and the General Ledger.

Instructions:

- Participants work in small groups
- Each group will be provided with sticky notes, markers, and a large sheet of paper.
- Prompt:

A.) Reflect on the AI Generated summary pertaining to VAT (LU3). How did the summary support your understanding of this Accounting concept pertaining to VAT? Write down your response on the sticky notes provided.

The below question is an example of the type of application question you would have been exposed to in ACC1A.

B.) How did you connect your understanding of VAT from the AI Generated summary to an application question, such as the below, during the module?" Write down your response on the sticky notes provided

"ABC Trading is a registered VAT vendor and trades with other registered VAT Vendors. For the month of September 2025, only 2 transactions took place in the Cashbook payment journal, the following payments were made via EFT.

- ❖ *Paid Astron Energies Garage R2 300 for petrol.*
- ❖ *Paid Makro R12 500 for equipment.*

Record the following transactions in the cashbook payment journal below and show your workings for all VAT calculations where applicable (total the bank column)."

Name of Payee	Bank	Input VAT	Trading Inventory	Sundry Accounts	
				Amount	Details

1. Using the information you have written down on the sticky notes, create a concept map on the sheet of paper you have been given to show how the AI generated summaries helped you to understand content, link ideas, and develop skills in the above example
Here is an example of a concept map:

Group project brief → helped me understand the main requirements → linked with research articles we found → used in weekly team discussions → improved collaboration and planning → clearer grasp of deadlines and roles → developed teamwork and communication skills

C.) Reflect on the AI Generated summary pertaining to the General Ledger (LU?) "How did the summary support your understanding of this concept? Write down your response on the sticky notes provided.

The below question is an example of the type of application question you would have been exposed to in ACC1A. How did you connect your understanding of the General Ledger from the AI Generated summary to your actions/application during the module?

D.) How did you connect your understanding of the General Ledger from the AI Generated summary to an application question, such as the below, during the module?" Write down your response on the sticky notes provided

"Using the answer from the previous question to create a general ledger entry for the bank account
Additional information:

The following information was given at the beginning of the month

- Opening balance for Cashbook receipts: R25 000 no transactions were recorded in the cashbook receipts journal for the month of September.

- Bank balance on 1 September 2025. R5000"

Bank	

2. Using the information you have written down on the sticky notes, create a concept map on the sheet of paper you have been given to show how the AI generated summaries helped you to understand content, link ideas, and develop skills in the above example (e.g., "summary explained General Ledger → used in weekly quiz → better grasp of transactions")

E.) Follow-up: Each group presents their concept map.

3. What skills were involved in moving from understanding to application of ACC1A content?
4. Did the summaries support surface or deep learning?

****Record themes that emerge**

Activity 2: Critical Incidents Reflection

Objective: In this activity my intention is to identify specific moments when the AI tool either enhanced or impeded skills development.

Instructions:

- Each participant will be asked to reflect individually and write down responses to the following:
1. Describe a moment when the AI tool helped you understand something clearly or apply a skill (use the sheet of paper to write down key points that you can use to share)

2. Describe a moment when the AI tool was confusing, difficult/challenging to use, unhelpful, or misleading (use the sheet of paper to write down key points that you can use to share)

A.) In pairs or triads, share your experience and discuss what made those moments effective or ineffective.

B.) What skills were you using in that moment (e.g., problem-solving, critical thinking)?

C.) Did the AI tool shape your motivation or approach to the task?"

****Record themes that emerge and will facilitate a full group debrief.**

Activity 3: Ranking and Justifying Skills

Objective: In this activity my intention is to evaluate the perceived impact of AI tools on different types of skill development.

Instructions:

Provide students with a list of skills from the ACC1A module

- Critical thinking (interpretation of the context of the problem)
- Problem solving
- Recollection and comprehension of concepts
- Practical application (accurate calculations)
- Communication
- Time management

A.) In small groups, rank the top 3 skills you believe were most supported by using the AI-generated summaries and questions (**prompt students to consider the skills commented on in the concept map). Please use the sheet of paper to note the ranking and justification

B.) Each group presents and justifies their ranking.

Follow-up Questions:

1. Why do you think the AI tool supported [skill] the most?
2. Were any skills *not* supported? Why?
3. Did any skills develop indirectly through repeated use of the AI content?

****Record themes that emerge**

Activity 4: Comparative Analysis – Textbook vs. AI Tool

Objective: In this activity my intention is to understand participants' conceptual preferences and learning pathways.

Instructions:

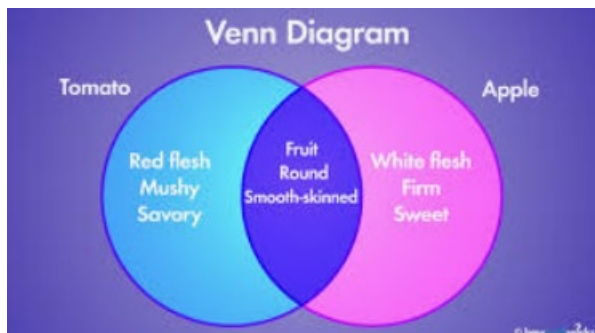
- I will provide excerpts from the recommended textbook and an AI-generated summary on the same topic.

A.) In groups, analyse and compare:

- Clarity of explanation
- Depth of understanding
- Usefulness for skill development (e.g., applying concepts, solving problems)

B.) Create a Venn diagram to highlight overlaps and distinctions providing justification

Example of Venn diagram



Discussion prompts:

1. Which resource helped you understand the learning outcomes better?
2. Which resource pushed you to think critically or solve problems more effectively?
3. How did this influence your preference (ie. to use the textbook or AI-generated resources)

Appendix 7: Example of Transcript

Respondent 13_Sbongakonke Madlala.m4a

Transcript

00:00:02 Speaker 1

Sbonga, thank you so much again for joining me today and for sharing your insights of your engagement with MathU in the first semester in your accounting module. So the first question that I'd like to ask is how did the AI generated lecture summaries that you got from MathU support your understanding of the key learning outcomes in the accounting 1A module.

00:00:29 Speaker 2

So with the with the App, in my personal experience I used it in the first, like 2-3 weeks. From what I gathered it would give a breakdown, like a summary of what we had done. But you know with Accounting it's more about numbers, so to give written notes that actually explains like step by step and so on, it helped in terms of just putting things into words.

00:01:13 Speaker 1

OK. Yeah. So you used it for those particular weeks in the semester. So would you say you only used it at the start of the semester and didn't really use it throughout the balance of the semester?

00:01:28 Speaker 2

Yeah, because our lecturer did bring it up, saying, "hey, guys, it's very useful" and so on and so forth and showed us how to use it, but for myself personally, I just thought that I already had enough learning resources. I didn't need a third or fourth source of information as much as it was useful. It's like I already have textbooks and slides. I don't need more. But for me personally, I was really doing well enough with the available resources. So it was just an extra thing.

00:02:05 Speaker 1

So was it a little bit overwhelming to have so many different resources? Would you say was that the feeling it was?

00:02:24 Speaker 2

I mean, I guess you could say so, cause you really have so many of them available. You've got, yeah, as I said textbooks and slides and things already given. But I guess you could use it to cut out everything else if you just use the App. I still think it was sufficient to pass Accounting 1A because it does like as I said, it explains things a bit more. See, it puts things in a more simple way to understand. But I just I relied more on my textbooks because it was just more like a guaranteed thing, you know that in the textbook it says, Test 1 will be like learning unit 1, 2 and 3. You know it's already there in the textbook and it's even got like questions to do, and that on its own is enough to pass all the assessments.

00:03:22 Speaker 1

OK. So would you say it was a preference then that you preferred to use your textbook than to use the Mathu App?

00:03:34 Speaker 2

Yeah. Also, because it's just on my phone when I'm studying. I don't want my phone out while I'm studying because I end up doing other things. So even though the summaries might be good, I'm not going to use them if I have to be on my phone. It's not productive for me personally. Not everyone wants to study on their phone. Some of us prefer laptops. If there was a web version or app for laptops, I'd use it more because I do most of my serious studying at my desk, not on my phone.

00:03:57 Speaker 1

You would have found it a distraction if I were to summarise it that way?

00:03:34 Speaker 2

Yeah

00:04:06 Speaker 1

OK. Well, that's interesting feedback. So thank you so much.

For the summaries that you did look at, in what ways was engaging with the summaries different to engaging with the textbook and module guide? In other words, were there any particular concepts that you felt it explained better than what you would have found in your textbook?

00:04:22 Speaker 2

I think so because now the textbook also does use like very formal language, like it will give you a three page answer for something that could have been said in like a paragraph or like even a couple of lines. Something like the summaries themselves, which is a whole lot more helpful, but yeah.

00:04:47 Speaker 1

OK. Did you find that they were easy to use? Was it easy to access the summaries and to use it? Was it user friendly?

00:04:57 Speaker 2

Yes, it's like helpful cause you just click on the thing, it gives a bit of notes and there's a couple of questions afterwards and then yeah.

00:05:05 Speaker 1

So you made a comparison just now between the textbook and MathU, and I think from what I gathered from your response, as you said, the language was not as formal as what you'll find in your textbook. What else?

00:05:46 Speaker 2

Yeah, That's about it. Because you know that textbook, they'll like explain a concept and then this is the person that theorised it, in this year. It's like I don't need this to pass this test. But like, it's all there and then they tell you about the different standards that have been since, you know, whatever and why they were established and like none of this is relevant. But hey, thanks, for letting me know. But then, yeah, I think the app did give me what I need instead of all the extra, just "waffling" on in the textbook.

00:06:16 Speaker 1

So was to the point and gave you the information exactly how you needed to prepare for your assessment?

00:05:46 Speaker 2

Yeah

00:06:24 Speaker 1

OK, fantastic. OK. Well, that's great feedback. So we've spoken now about the summaries, but obviously MathU also generated questions, some were in the form of multiple choice and others were quiz kind of activities. Please describe the way in which the homework questions may have helped you to think more deeply about Accounting terms you were taught in class.

00:06:55 Speaker 2

I don't think I did enough to give a meaningful answer because it is a thing of every now and again I'll remember, oh, I have this app on my phone and then I check maybe do a quiz or two, but yeah, that's about it, that's my personal experience.

00:07:13 Speaker 1

OK and that's absolutely fine. But in saying that, it's also important for me to understand, you know, why wouldn't you have engaged with it a lot more and my sense from your earlier response was that you felt you were getting enough from your textbook and therefore you didn't feel the need to use the questions. Is that a correct understanding?

00:06:55 Speaker 2

Yeah.

00:07:13 Speaker 1

OK. And the questions that you did use the brief times that you went onto do it, in what way did it add value in any way to your learning?

00:07:58 Speaker 2

So with the App actually simplifying the notes, the questions themselves end up being a bit too simple because it's not the same level as what we get asked in the assessments. I guess like it's useful and it helps, you know, these things, but it's not challenging or enough to be worthwhile. If I'm gonna be honest. I think it would help at like the grassroots level because it does give very basic, very simple explanations, which is awesome when you're still trying to grasp the concepts. But once you're comfortable and you need to know the more challenging aspects of it, it's not going to be of much help. The questions don't ask you to analyse anything. They don't ask 'Why would this transaction affect this account?' or 'What's the difference between these two Accounting treatments?' Those deeper questions would help you really understand, but the AI doesn't ask them.

00:08:41 Speaker 1

OK. Well, that's good. That's good to know. And that's good feedback. So just based on you finding that the questions were not challenging enough, if you were to provide any insight in terms of whether these resources supported your understanding of concepts versus application of concepts, where would you say it helped you and why?

00:09:12 Speaker 2

There were some questions that asked you to prepare a simple journal entry or classify accounts. So you had to apply what you learned, not just remember it. But the questions were basic, much simpler than textbook exercises or exam questions. I think it would help at like the grassroots level because it does give very basic, very simple explanations, which is awesome when you're still trying to grasp the concepts. But once you're comfortable with something, I think you'd look at MathU when you're just like completely in the woods because then it's like, OK, this is in simple terms for maybe this section or journals, or whatever it may be, but once it's a thing of or you're really comfortable doing journals or whatever section and now it's like the more challenging aspects of it, it's not going to be of much help.

00:09:49 Speaker 1

OK. And did you do accounting at school or was this your first time being exposed to accounting.

00:09:56 Speaker 2

It's my first time doing Accounting, I didn't do it at school.

00:09:56 Speaker 1

Were the questions and the summaries relevant to what was being taught to you in class? And how did it influence your learning?

00:10:24 Speaker 2

Yes, yes, yes, very much so. It was just the aspect of them being a bit, because I don't want to say it's too plain because it's a good thing that is like simple to grasp, but I also, I don't need something explaining basic concepts to me.

00:10:43 Speaker 1

You wanted it to be a bit more challenging?

00:10:24 Speaker 2

Yeah. I don't need something explaining basic concepts to me at this point in the semester. I need progressively harder questions that build from simple to complex. Like start with a basic transaction, then add complications, then combine multiple transactions, then introduce scenarios requiring judgment. The AI stayed at the basic level throughout, which stopped being useful after the first few weeks.

0:10:46 Speaker 1

I get you, OK. I'm just looking through my questions to see what else is necessary to ask at this particular point in time. OK, so if you consider skills, things like critical thinking, problem solving, etcetera, do you think that the way in which this tool was incorporated into the module, did it lend itself to developing any of those skills and in what ways did it influence the development of skills?

00:11:42 Speaker 2

Yeah. I can't really say it did, it wasn't. Because I don't know, it was insignificant, cos that's a bit harsh, but, yeah in terms of critical thinking, not at all, yeah.

00:12:03 Speaker 1

It's okay, I want your honest feedback, so please don't hold back.

00:12:09 Speaker 2

I don't wanna completely say it is useless because there were certain things like, OK, that it did clear a few things up, but there's no major like leaps and bounds that it made in like my understanding of anything.

00:12:24 Speaker 1

All right. So in terms of your academic performance, I mean, just based on the responses you've provided already, it doesn't appear as though you as a student would have felt that the app supported or improved your academic performance within the module. Would I be correct in saying that or how did the tool influence your overall academic performance?

00:12:46 Speaker 2

Yeah, I feel like I did look to it a couple of times, but it wasn't something I relied on. It did have somewhat of an impact, but nothing significant that I could say, hey, this is what got me through the semester. It tells you the steps, which is good, but then you need to practice those steps many times with different examples. The pathway questions didn't give enough practice, and they were too simple compared to what we had to do in exams.

00:13:05 Speaker 1

So would you say that it really just helped in terms of clarifying certain concepts for you that helped your understanding.

00:12:46 Speaker 2

Yeah it helped with concepts. But the questions. The questions are like true or false or asking about terminology, but in the test we have to do calculations and prepare accounts. So it doesn't help to practice true/false questions when that's not what's being tested.

00:13:17 Speaker 1

OK, so if you were to give me a wish list, considering your experience now with working with MathU in that Accounting 1A module, and you were to create this wish list of what an AI tool should do to really, you know, give you value within a module like accounting. What does the ideal AI tool look like to you? What should it do? What are some of the functionality you would like it to have, where it would be seen to be valuable and impactful to your academic performance in your learning.

00:13:50 Speaker 2

Audio playback. Our generation doesn't like to read, rather hear or watch videos. Before tests and exams, I watch videos to get a better understanding of something. I'm not gonna go read something new. I'm gonna go either watch or listen to something. And then just go back to my current resources and do you like examples of like past papers, whatever, maybe. But I'm not going to go and read new information. It's very unlikely. I think even maybe, if it could generate like potential like question papers, like proper activities, like tests that you could do, that would be very helpful. You know just to be like in this module, this is what you'd be expected to be able to understand in order to pass and that gets you through the module comfortably, that would be

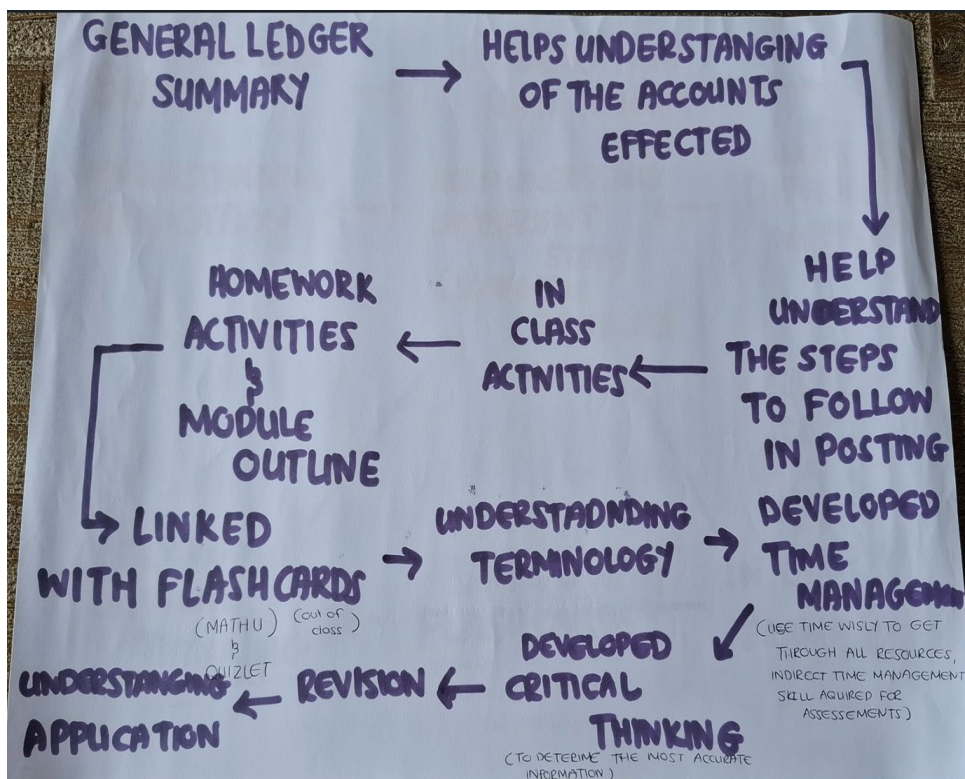
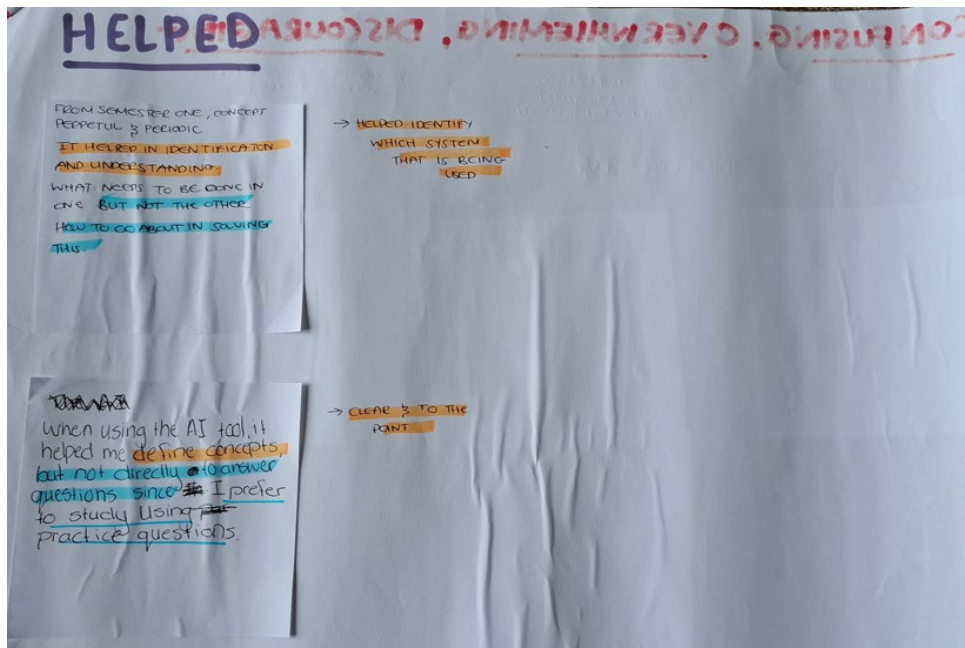
a huge benefit because it doesn't help to get a summary of what the section is and then get like 4 questions that are like true or false or ask about terminology, or they'll have very basic calculations because it's not what's going to be asked in the test. So it's not going to be of much use to me. So yeah, if the generic questions that are more challenging that are absolute standard that we are being tested at, audio playback or if it could just read to you what the notes are actually saying, then at least you could just put that aside, do or write, or whatever. The notes being simple are fine. But I feel with more challenging questions there would have to be more deeper explanations.

00:16:23 Speaker 1

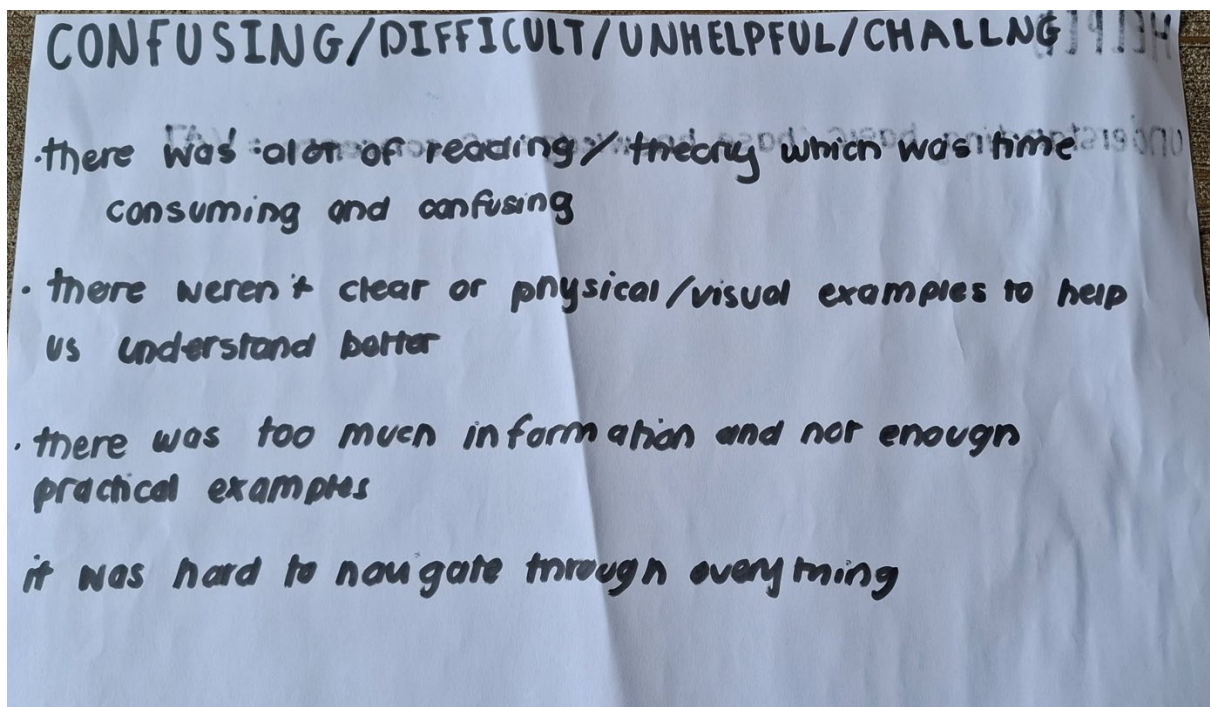
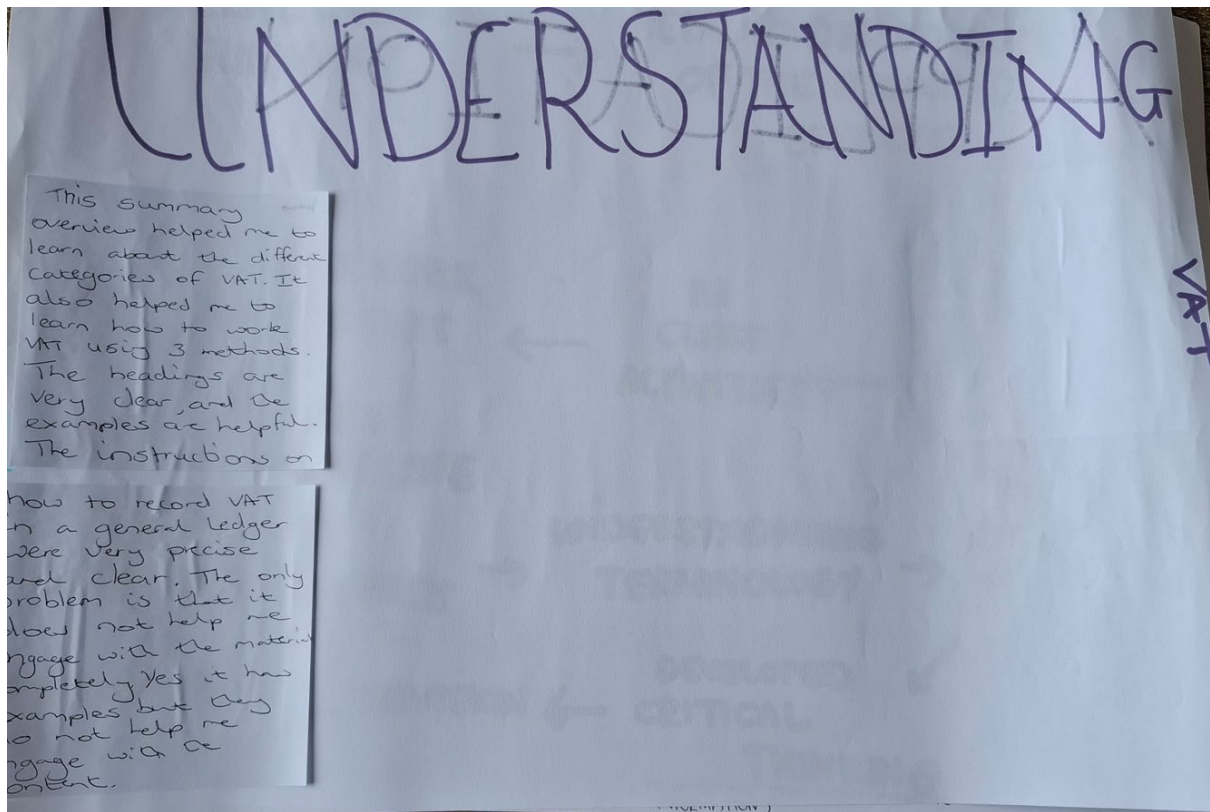
OK. OK. Well, thank you so much. I mean, your responses were really valuable. I appreciate the insights that you've shared this afternoon.

Appendix 8: Examples of artefacts from focus group activities

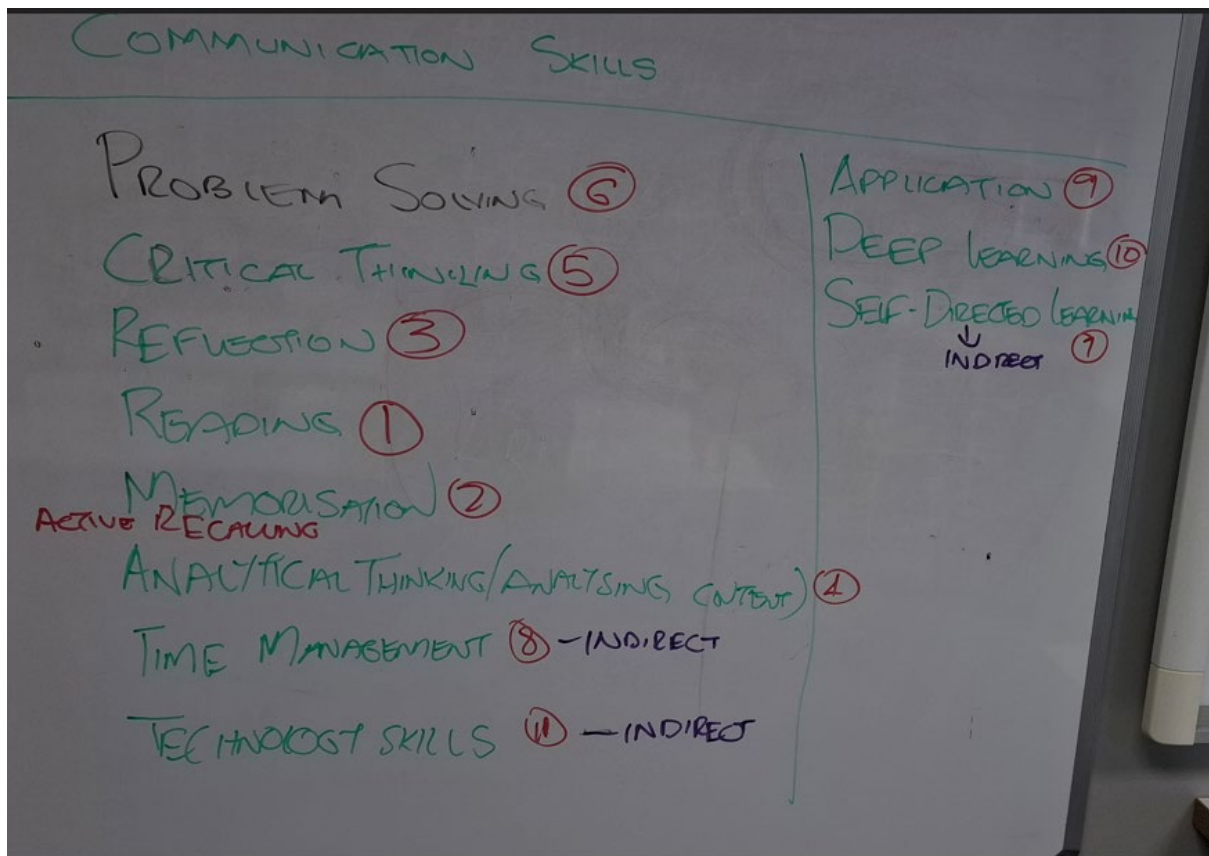
Activity 1



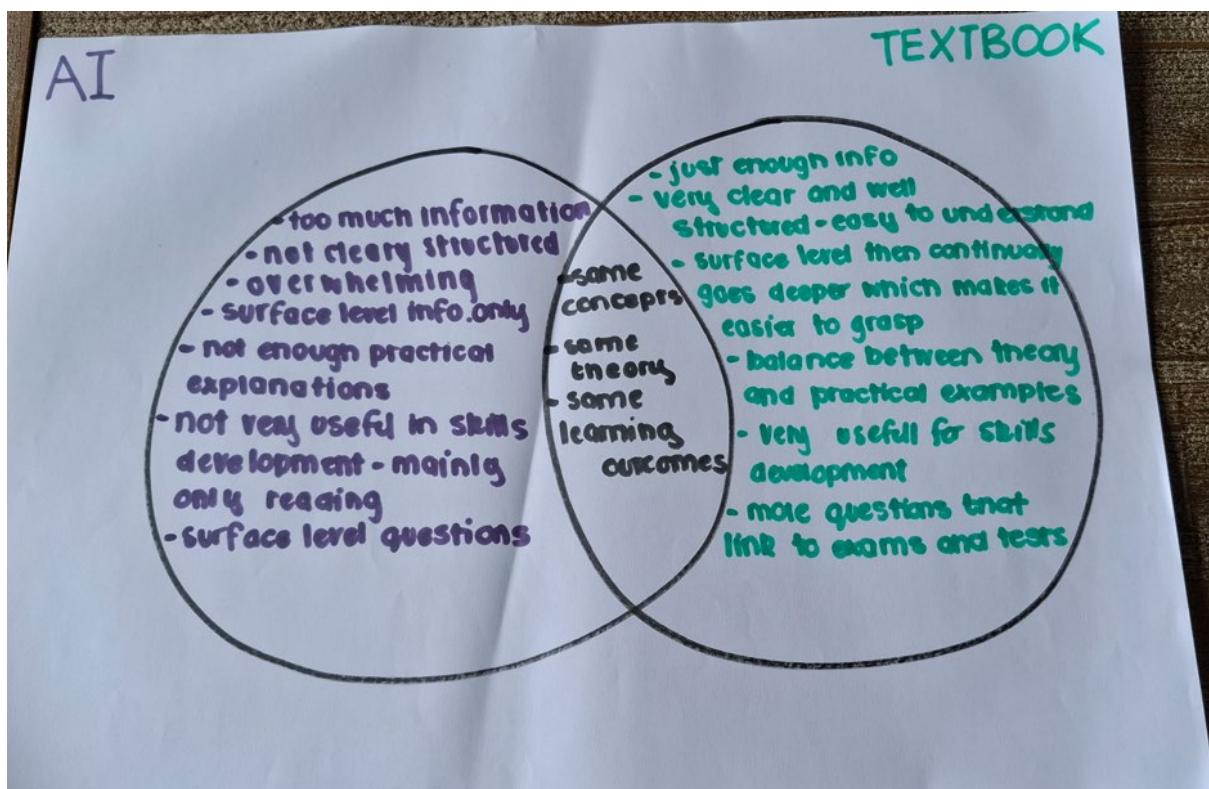
Activity 2



Activity 3



Activity 4



Appendix 8: Module Outline (ACC1A)

Module Purpose	
This module covers the concepts and principles of appropriate accounting frameworks, and policies. The module provides you with the applied competence to orderly and systematically identify and record monetary value of business transactions.	
Module Outcomes:	
MO1	Explain the development, role, and functions of accounting as a Business Information System
MO2	Demonstrate an understanding of accounting principles and concepts in a business environment
MO3	Apply the accounting equation and its composites when recording transactions
MO4	Accurately record financial transactions to trial balance
MO5	Demonstrate an understanding of statutory requirements in a business environment

Appendix 9: Turnitin Report

Final Dissertation Eve Reddy for TURNITIN.doc

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