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Exploring the effects of Women in Artificial Intelligence Networks (WAINs) on women's careers in Artificial Intelligence

By

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Declaration

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To all the remarkable women in the field of AI, with a special mention to the leaders of the WAI network, your time and generosity are greatly valued - keep charging the way!

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Abstract

The underrepresentation of women in the AI field is one of the causes of AI application biases needing resolution as part of the growing movement toward more ethical AI. One potential solution is to encourage more women to be involved in developing and deploying AI solutions, precipitating the growth of professional women in AI support networks. This research aimed to determine how women in AI networks contribute to women advancing and persisting in the AI workforce by developing and testing a model that links networking behaviour to women's career persistence and advancement in AI. The study addressed the need for theoretical and empirical investigation into women in AI, networking behaviour, and the benefits networks offer to members, especially for their careers. Notably, there is a gap in the literature concerning formal women-only networks, with limited previous research on gender bias in the context of women in artificial intelligence networks (WAINs).

The study followed a phased mixed method research process. First, a systematic review of AI gender bias was conducted, which supported the premise for increased gender diversity in AI. A conceptual model was then created from an intersection of multiple theories and models on gender in IT and networking, which a panel of women in AI experts reviewed, verified, and refined through in-depth interviews. The final phase tested the model propositions using structured equation modelling. The findings revealed that social support, opportunities and resources provided by professional WAINS contribute to the persistence and advancement of women in AI careers. This research provides an original contribution by suggesting a solution for improving gender diversity in AI development teams through the resources, opportunities and social support provided by WAINs. The research also contributes to a better understanding of women's careers and networking behaviour specifically in the AI field. With the proliferation of AI-based solutions and the integration of AI into automated decision-making, reducing the gender gap in the AI workforce is more important than ever. Recommendations include active support for WAINs by businesses and policy bodies, while WAIN organisers and women in AI should co-create career enhancing resources and support in WAINs.

Keywords: AI career advancement; AI career persistence; AI gender bias; women in AI; women in AI careers; women in AI networks.

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Chapter 1. INTRODUCTION

1.1. Introduction to the Study

Artificial Intelligence (AI) is rapidly and fundamentally changing many business models, industries and the nature of work itself. At the heart of the AI revolution are predictive algorithms, developed predominantly by men and trained on data sets with inherent gender biases (Alzubaidi et al., 2023, p. 2; Bourton, Lavoie, & Vogel, 2018, p. 45; Foulds, Islam, Keya, & Pan, 2020, p. 1918). These algorithms are used for automated decision-making in management applications as wide spread as employment, access to credit, advertising and health (Bartlett, Morse, Stanton, & Wallace, 2019, p. 21; Bourton et al., 2018, p. 90; Chen, Ma, Hannák, & Wilson, 2018, p. 1; de Kleijn, Siebert, & Huggett, 2017, p. 10; Hoffman & Friedman, 2018, p. 17; Varsha, 2023, p. para 6). Recently, ethical issues, such as bias and toxicity, have arisen around generative AI, including large language models such as ChatGPT (Zhuo, Huang, Chen, & Xing, 2023, p. 1). The extent of the bias led to some early AI applications being withdrawn, such as Amazon and LinkedIn's AI-based resume services that only sent IT job openings to male job seekers (Varghese, 2019, p. 1; West, Whittaker, & Crawford, 2019, p. 9). Regulators investigated Apple's new credit card after finding the algorithm for creditworthiness was granting higher limits to men than women with the same credit rating (Vincent, 2019, p. 1). Research has supported these anecdotal biases; for example, a recent study entitled "Computer algorithms prefer headless women" showed how advertising algorithms demonstrate sexist tendencies when it comes to images used in online targeted marketing (Cecere, Jean, Manant, & Tucker, 2018, p. 1).

AI gender bias has been attributed to the underrepresentation of women in AI development teams and training data sets, which in turn perpetuates gender imbalances, often in opposition to international legal and ethical management practices (Bourton et al., 2018, p. 45; Yapo & Weiss, 2018, p. 5366). An established issue in AI adoption is that bias can inadvertently be introduced, resulting in automated discrimination (Zhuo et al., 2023, p. 1). Consequently, there have been increasing calls for solutions to the problem (Dillon and Collett 2019, p.25). One pragmatic solution is improving diversity among the people in AI development teams (Schwartz et al., 2022, p. 37). However there is a persistent gender gap of 72% in the AI profession

(Stathoulopoulos & Mateos-Garcia, 2019, p. 5; WEF, 2018, p. 32). If more women are involved in developing and deploying AI solutions, more equitable distribution of the benefits of AI will result (Shams, Zowghi, & Bano, 2023, p. 24). However, many women tend to leave the AI and general information technology profession, citing hostile, unsupportive and masculine work environments and lack of equity and leadership opportunities, among other reasons for leaving (Ashcraft, McLain, & Eger, 2016, pp. 15, 34; Nesaratnam, Mamba, & Singh, 2018, p. 155). Many internal business attempts to improve gender representation, for example, through specialised diversity and inclusion programmes, have failed to close the gender gap (Dobbin & Kalev, 2016, p. 52). External, long-term and sustainable interventions are more likely to be of benefit (Gorbacheva, Beekhuyzen, vom Brocke, & Becker, 2019, p. 50); specifically, networks supporting women in AI have been suggested as a potential solution (Wittemeyer, 2018, p. 65). Such professional networks to support women in AI have arisen and have received global support and rapid membership gains (WAI, 2022, p. 3). However, whether these networks effectively encourage career persistence and advancement for women in AI is currently unknown.

This chapter provides context for the study, starting with background to the research issue of bias in artificial intelligence (AI). A discussion of the research problem follows, culminating in the overall research objectives and questions. Next, the three phases followed in this research are explained, including how each phase results in a paper for publication. Ethical considerations are then outlined, followed by the rationale for the research and the study's benefits and relevance in the contribution section. The chapter concludes with the structure of the thesis.

1.2. Background and Motivation for the Study

Artificial intelligence has many use cases for business and society in general. The rapid adoption of large language models such as ChatGPT has demonstrated the usefulness of machine learning beyond areas of AI, such as machine vision and robotics (Zhuo et al., 2023, p. 1). With more people and businesses relying on AI output to increase productivity and inform or automate decisions (Akerkar, 2019, p. 6), the output must be unbiased, reliable and accurate. However, biased output is common and widespread (Varsha, 2023, p. para 9). Awareness of bias in this output has increased, and several commentators, politicians and community action groups have

warned about AI model reliability and the potential harm of biased output (Zhuo et al., 2023, p. 2), for example, in determining credit-worthiness, healthcare, recruitment and pricing (Varsha, 2023, p. para 13). AI bias is an established research agenda (Weiyu & Keng, 2019, p. 71), and is a top common risk across sectors of AI use (Varsha, 2023, p. 1). Many companies and researchers are working on issues related to algorithmic bias, however, the research is fragmented and conducted from multiple disparate perspectives, from intersectional studies to technical machine learning algorithms to AI ethics policy initiatives.

AI models generally produce output without being transparent about how the outcome has been derived or reasoned, the so-called 'black box' approach (Varsha, 2023, p. para 2). The output can contain obvious or subtle bias, particularly gender and racial bias (Ferrara, 2023, p. 1). All types of bias are problematic, but the variability and consequences differ; therefore, not all can be addressed simultaneously to do justice to the issue. Gender bias is one prevalent type of bias that should be studied in the context of AI-generated solutions . When the output of AI models is used for automated decision-making involving women and gender minorities, this can have far-reaching consequences (Schwartz et al., 2022, p. 9).

Particularly with machine learning, gender biases in the training data used to develop the AI models inevitably manifest in the model output unless the problem is proactively and specifically addressed (Nemani, Joel, Vijay, & Liza, 2023, p. 2; Schwartz et al., 2022, p. 10). The training data is sourced from human-generated data, mainly from the Internet, where gender bias in the worst forms is prevalent. Human-generated data naturally reflects their values and attitudes, which, if reflecting inherent gender bias, can translate into these biases becoming part of the AI model (Lainjo, 2023, p. 4969; Varsha, 2023, p. 10). Biases in the real world should not be replicated in the digital world since the consequences are non-trivial, potentially impacting the sustainability of businesses, the livelihoods and futures of women and gender minorities, and ultimately impacting society negatively, for example, when voice recognition misrecognises women and when AI-generated advertising stereotypes women's role in society (Waelen & Wieczorek, 2022, p. 52).

The significance of gender equity is highlighted when considering it is goal 5 in the United Nations sustainability development goals, yet AI amplifies gender discrimination

due to the gender gap in the AI workforce (Schulenberg, Watkins, Hauptman, Schlesener, & Freeman, 2023, p. 183; Vinuesa et al., 2020, p. 3). Additionally, methods to improve gender equity in AI at all career stages have been adopted as policy by United Nations Educational, Scientific and Cultural Organization (UNESCO, 2021, p. 32). Further, UNESCO have an inclusiveness in AI design goal (UNESCO, 2020, p. 14). The World Economic Forum have also highlighted the need to reduce the gender gap in AI so that AI systems are designed to have a positive rather than negative impact on society (WEF, 2018, p. 30). Additionally, the issue is not restricted to the private sector with concern related to systemic bias, oversight and accountability being raised in the public sector (O'Connor & Liu, 2023, p. 4).

While AI ethics and biases are a compelling problem, improving diversity among the people in AI development teams is one pragmatic solution (Cairns, 2019, p. 5). However, the field of AI is dominated by men, with women comprising only 22% of the AI workforce (Kawamoto, 2019, p. 1; McDonald, 2018, p. 1), with even lower percentages in AI research (Stathoulopoulos & Mateos-Garcia, 2019, p. 5) and education (McDonald, 2018, p. 1). As promulgated by UNESCO (2021) in their recommendations of AI ethics, female representation must be encouraged in all AI lifecycle stages to reduce discrimination and gender stereotyping in AI systems.

Diversity and inclusion (D&I) policies within companies were introduced as a potential solution (West et al., 2019, p. 13), where D&I is defined as "'inclusion' of humans with 'diverse' attributes and perspectives in the data, process, system, and governance of the AI ecosystem" (Shams et al., 2023, p. 2). However, these policies have mostly failed to improve diversity (Dobbin & Kalev, 2016, p. 52). Other attempts include creating networks within the organisation, to provide support for women, however these attempts have also been met with limited success (Villeseche & Josserand, 2017, p. 1007).

Rather, external, formal professional networks are needed, as they provide the resources, knowledge and contacts necessary for career success (Bapna & Funk, 2021, p. 595). Such networks are driven from the employee side, which is especially pertinent, given the rise of career self-management, where the individual takes charge of their career development (Fryczyńska & Ivanova, 2019, p. 212). There is also the potential for more extensive benefits for women who belong to formal networks, since

women are often excluded from informal networks (Villeseche & Josserand, 2017, p. 1008), especially in the IT sector where there are so few women (Bapna & Funk, 2021, p. 594).

Several voluntary, professional women's networking groups have formed in response, for example Women in Artificial Intelligence, a network of over 8000 members from 140 countries (WAI, 2022). Other more specialised networks include Women in Machine Learning, Women in Robotics and Women in Voice. Formal networks both within the place of employment and external profession-based networks have been linked to improved career support and performance (Hampton, Cooper, & McGowan, 2009, p. 15; Wolff & Moser, 2009, p. 17). Further, professional networks can improve women's job satisfaction (Macintosh & Krush, 2014, p. 2630). However, there is little research on formal networks for women, (Annabi & Tari, 2018, p. 5152) especially for women in the AI profession.

1.3. The Research Problem

Since AI is predicted to cause unprecedented disruption (Lainjo, 2023; Soni, Sharma, Singh, & Kapoor, 2019, p. 2), it is essential that businesses, governments and society ensure that discriminatory practices from the past are not built into the AI systems of the future (West et al., 2019, p. 19). Algorithmic bias has caused harm to marginalised societal elements, including women and non-binary minorities (Leavy, Meaney, Wade, & Greene, 2020, p. 2; Saka, 2020, p. 2) necessitating technical and social solutions (Draude, Klumbyte, Lücking, & Treusch, 2019, p. 334; Selbst, Boyd, Friedler, Venkatasubramanian, & Vertesi, 2019, p. 8). Bias against women in AI solutions is a manifestation of the underrepresentation of women in data sets used to train algorithms, and the lack of gender diversity in AI development teams (Nadeem, Marjanovic, & Abedin, 2022, p. 7). Biased solutions then perpetuate and amplify gender imbalances, creating a feedback loop that furthers discriminatory AI solutions (Ferrara, 2023, p. 2; Wellner, 2020, p. 129).

Increasing women's participation in AI development teams is a practical and ethical priority to reduce algorithmic bias in AI solutions, thereby ensuring a fairer distribution of the benefits of AI (Leavy, 2018, p. 3). However, women are less likely to persist and

advance in AI careers, resulting in a detrimental gender gap in AI careers that needs solutions (West et al., 2019, p. 3). Although there is a lack of women at all stages of the career pipeline, from entry to leadership positions (O'Connor & Liu, 2023, p. 251), the lack of representation of women in the AI profession particularly requires support for women to remain and advance in the field (Roopaei et al., 2021, p. 502). This need has precipitated the growth of voluntary, non-profit professional support networks for women in the form of Women in AI Networks (WAINs). The extent to which these networks can assist women in advancing and persisting in the AI field is worth investigating, given the importance to the future of women not just in AI but whose lives will be affected by AI (Lainjo, 2023, p. 4967; West et al., 2019, p. 15). There is a paucity of research into these networks, as little is known about women-only networks and membership benefits and there is a lack of theoretical underpinning (Villeseche & Josserand, 2017, p. 1006) Specifically, how these networks support women in AI professionals in persisting and advancing their careers is currently unknown.

This research aims to determine how women in AI networks support women in advancing and persisting in the AI field and to develop and test a theoretically sound model that links networking behaviour and usage to the career persistence and advancement of women in AI.

1.4. Research Objectives

Primary objective: To explore how WAINs support women in advancing and persisting in the AI field.

The following objectives address the research problem and overall research purpose.

Objective 1: *To conduct a systematic, interdisciplinary review of the current state of research on algorithmic gender bias.*

This objective provides an impetus for the overall research purpose, by seeking to provide an assessment of the causes, consequences and solutions to AI bias to better understand the extent and nature of the problem.

Objective 2: *To develop a model of women in AI networking and career persistence and advancement.*

This objective relates to the overall research purpose to provide structure for

establishing a relationship between networking and women in AI careers. The intention was to develop a conceptual model from literature, and then refine and test the model.

Objective 3: *To investigate women's career persistence and advancement in the AI profession*.

This objective involves exploring expert opinions on women in AI careers and determining WAIN members' career persistence and advancement.

Objective 4: *To examine women in AI networking behaviour.*

Similar to objective 3, this objective involves exploring expert opinions on women in AI networking behaviour and determining WAIN members' network behaviour.

Objective 5: *To explore Women in AI Network (WAIN) benefits and resources.*

This objective relates to understanding the benefits of and resources provided by WAINs, both from the expert opinions and WAIN members perspectives.

Objective 6: *To determine the relationships between networking behaviour and career persistence and advancement.*

This final objective ties together the previous objectives to satisfy the overall research purpose, which is to investigate how women in AI networks contribute to women in persisting and advancing in the AI field.

1.5. Research Questions

Primary research question: How do WAINs support women in advancing and persisting in the AI field?

Related to the research objectives above are the following research questions and sub-questions.

RQ1: *What is the current state of research on the social causes and consequences of, and solutions to, gender bias in AI?*

- RQ1a: What are the social causes of AI gender bias?
- RQ1b: What are the consequences of AI gender bias?

- RQ1c: What social solutions are there to gender bias in AI?

RQ2: *How does networking in WAINs impact career persistence and advancement?*

RQ3: *How are women in AI persisting and advancing in the AI profession?*

- RQ3a How are women in AI persisting in the AI profession?
- RQ3b How are women in AI advancing in the AI profession?

RQ4: *What networking behaviour do members of WAINs display?*

RQ5: *What benefits and resources are offered by WAINs?*

RQ6: *What are the relationships between networking behaviour and career persistence and advancement for women in AI?*

The development of the hypotheses and conceptual model are detailed in Chapter 2.

1.6. Three Phased research study

To achieve the objectives and purpose of this study, and to answer the research questions above, a three-phased study was conducted. *Phase One* of the research was a systematic review, as a 'stock take' of the causes, consequences and proposed solutions of algorithmic gender bias. This review pulled together research from disparate disciplines to fully understand the problem of algorithmic gender bias within a socio-technical framework. *Phase Two* fully developed and justified an initial conceptual model for studying the effects of WAINs on women in AI's career persistence and advancement, which was then interrogated with an expert opinion study conducted with industry and academic experts who are leaders in WAINs, networking or AI ethics. *Phase Three* was to test the model quantitively to provide a detailed analysis of the nature of WAINs and to establish the model's validity for further research in other networks.

1.7. Research Methodology Overview

Traditionally positivism and interpretivism have been regarded as the standard but opposite approaches to research, with positivism associated with quantitative research and interpretivism with qualitative research (Ivankava, Creswell, & Plano Clark, 2007,

p. 259). Each of these paradigms offers a distinct perspective on the research problem. Viewing the research problem with an interpretivistic lens makes an in-depth understanding of the issue possible, while positivism allows relationships to be tested and the possibility of generalising the results (du Plooy-Cilliers, Davis, & Bezuidenhout, 2021, p. 28). Combining both provides a more nuanced investigation of the research problem, as is required for the nature of the topic of women in AI and the phased approach taken with this research. Pragmatism is the research philosophy commonly associated with a mixed approach, which contends that quantitative and qualitative research are compatible and allows for a more comprehensive analysis (Ivankava et al., 2007, p. 262), as required with this research study. Villeseche and Josserand (2017, p. 1008) contend that formal women networks should be researched both qualitatively and quantitatively. According to Ivankava et al. (2007, p. 261), a valid reason for conducting mixed methods research is to use qualitative data to develop a new model and then to test the model quantitatively, which is the general approach for this research.

The research was divided into three phases:

Phase 1

The first phase sought to validate the need for and importance of the research and to develop a comprehensive understanding of the causes, consequences and proposed solutions by conducting a systematic review of AI gender bias. The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) protocol was selected since it is the preferred method for ensuring a rigorous review and is used by other systematic reviews on the topic of algorithms (e.g. Favaretto, De Clercq, & Elger, 2019, p. 4; Wieringa, 2020, p. 1). Arguments that systematic reviews are not helpful in an immature field such as gender bias in AI algorithms are countered by Petticrew and Roberts (2008, p. 35), who suggest that such reviews are suitable to identify gaps, research directions and potential early interventions. The review provided a comprehensive, cross-disciplinary understanding of the social causes and consequences of gender bias in AI, and proposed solutions that help to identify research trends related to AI bias. The need to support more women in AI was a significant outcome, that provided impetus for Phase 2.

Phase 2

With the research purpose validated and an in-depth understanding of the AI gender bias phenomenon established, the purpose of Phase 2 was to fully develop and justify a conceptual model based on theory as recommended by Creswell (2009, p. 208). An initial model was developed using secondary research, where various theories and literature on women in IT and networking were explored and integrated. This model was interrogated and refined through a qualitive, exploratory design (Ivankava et al., 2007, p. 265), based on expert opinion with industry and academic WAIN experts. The outcome was a testable model based on the original conceptual model and completed with the data analysis from Phase 3.

Phase 3

Finally, Phase 3 tested the model quantitatively to provide a detailed analysis of the nature of women in AI networks and the relationships between WAIN member networking behaviour and their career persistence and advancement in the AI workforce to establish the model's validity. Structured equation modelling was used to determine the impact of networks on women in AI careers.

Figure 1 outlines the three phases of the research.

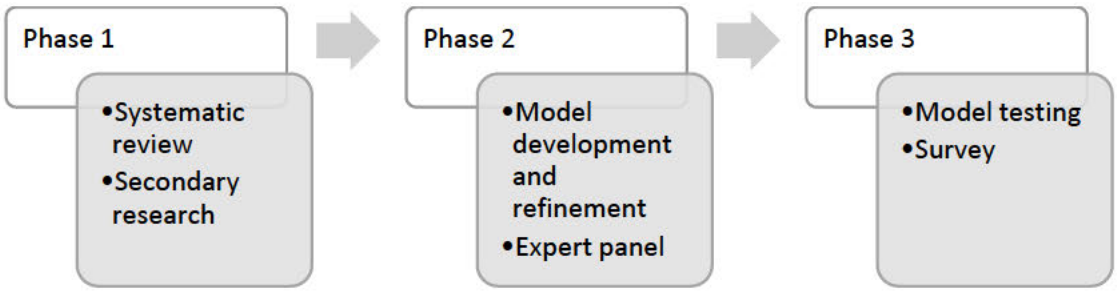

Figure 1 Three-phased research design

The design is thus multi-phase exploratory sequential (Ivankava et al., 2007, p. 265). The advantage of this design is that it increases the contribution of the research, as the model will have undergone multiple tests and is grounded in theory and data (Creswell, 2009, p. 212). The design was cross-sectional as the interviews and surveys were once-off rather than over an extended period (Bhattacherjee, 2012, p. 39). There was no mixing of the data, but rather the data analysis results from one phase connected with the data collection in the next phase (Creswell, 2009, p. 208).

Phases 2 and 3 involved primary research, with Phase 2 being qualitative and Phase 3 quantitative; thus, the design approach was notationally: QUAL -> quant (Creswell, 2012, p. 538). This design was necessary because the network outcome variables in the model were unknown, and there was no model to fully explain women in AI networking and its relationship to career outcomes. As suggested by Creswell (2012, p. 544), model validity should be tested quantitatively.

Table 1 below summarises the population, sampling and data collection methods for the primary research phases, with full details in Chapter 3.

Table 1 Primary research design elements

Phase	Methodology	Population	Sampling	Data collection method	Data Analysis
2	Qualitative	Women in AI experts	Purposive	Semi-structured interviews	Content analysis with thematic coding
3	Quantitative	Women in AI network members	Census	Survey	Statistical, Structural equation modelling

1.8. Delimitations of the Study

The recruitment of women into the AI field was beyond the scope of this research. Although essential, recruitment is the subject of previous research, (e.g. Trauth, Quesenberry, & Huang, 2008, p. 2; Wang, Hong, Ravitz, & Ivory, 2015, p. 117), therefore not much value would have been added by including it in this research. This research was limited to retaining and advancing women in AI. Also outside the scope of this research was the effect of networks on organisational performance, networks within organisational boundaries, or the impact of informal networks. This research focused on external, professional, women-only networks for the AI profession.

Additionally, the research was on gender bias as a whole and did not focus more granularly on intersectionality, for example between race and gender, or between AI disciplines, for example robotics. Lastly, the study did not address differences between the global North and South or between the public and private sectors.

1.9. Ethical Considerations

Ethical Clearance was obtained from the UKZN research office for the three phases, evidenced in Appendix E. Permission for Phase 2 was obtained from the experts sampled to conduct the interviews, with written informed consent provided before the interviews took place. Phase 3 followed a similar ethical procedure but also included gatekeeper's permission from one of the WAIN leaders. Copies of the informed consent and gatekeeper's letters are in Appendix A and B respectively. By the nature of the topics and methodologies followed in the research, there was no harm to participants. Respondents were informed of the research purpose and that the nature of their participation was entirely voluntary and therefore that they could leave the study at any time. Strict ethical guidelines were observed in the analysis, interpretation and all reporting of findings. For example, only summarised results are presented ensuring individual confidentiality. Further, all data has been password protected and securely stored. Finally, all research ethical requirements per the UKZN research office have been complied with.

1.10. Justification/Rationale

Algorithmic bias attributed to the lack of women in AI is well established (West et al., 2019, p. 33); however, what can be done to solve this is an established research agenda and is a problem worth solving. This research proposes that AI networks, such as Women in AI, are a potential solution to keeping and promoting women in the field. Increasing gender inclusivity is part of the focus on ethical AI by businesses, international bodies and government initiatives supporting women (OECD, 2019, p. 17). Further, companies will benefit from AI output that is more inclusive and appeals to a diverse gender base which will ultimately improve their bottom line (Ashcraft et al., 2016, p. 16; Olbrich, Trauth, Niederman, & Gregor, 2015, p. 768).

Literature shows there is a lack of women in AI, with women in technology facing challenges with career persistence and advancement. Yet, there is little theoretical or empirical research into causes and solutions for this (Armstrong, Riemenschneider, & Giddens, 2018, p. 2). There is a research gap around the consequences and impact of interventions on the lack of gender diversity in IT as a whole (Gorbacheva et al., 2019, p. 45). Gorbacheva et al. (2019, p. 51) recommend further research into support systems for women in IT, of which networks such as WAINs are examples.

Further, operationalising and testing theoretical constructs related to women in IT is lacking, with triangulation and rich mixed methods research required (Gorbacheva et al., 2019, p. 49; Trauth, 2013, p. 288). The under-theorisation is blamed on the lack of research into and application, development and testing of, existing theories to add more substance and insights instead of continually developing new disparate theories (Gorbacheva et al., 2019, p. 52; Trauth, 2013, p. 278). This research sought to develop, refine and test a theoretically sound model developed from existing theories, that links networking behaviour and usage to women in AI career persistence and advancement.

1.11. Contribution of the Study

This research answers the call for further research into the impact of women in technology networks, interventions to improve diversity and inclusion, and to focus on non-technical factors in AI bias (Annabi & Tari, 2018, p. 5152; Gorbacheva et al., 2019, p. 46; West et al., 2019, p. 18). The results of this research will be helpful to national and international efforts to reduce bias in AI, increase inclusivity, and improve the growing field of ethical AI (OECD, 2019, p. 17). Each phase of the research, through a paper submitted for publication, contributes to the body of knowledge. The systematic review of the current status quo in AI gender bias provides a cohesive analysis of research from a socio-technical viewpoint, which was previously unavailable. Petticrew and Roberts (2008, p. 15) argue that systematic reviews provide evidence-based analysis and synthesis of previous studies, creating an overall picture of the topic. In software engineering, systematic reviews offer a clear picture of the latest, state of the art research (Kitchenham & Brereton, 2013, p. 2067), which is pertinent to gender bias in AI algorithms. The results of the systematic review were

accepted for publication in Online Information Review, a first quartile journal (Hall & Ellis, 2023).

In a report proposing future research in AI and gender, Dillon and Collett (2019, p. 27) recommended diversity in AI careers as a central research theme as diverse AI development teams reduce AI bias. This research fits within that theme and answers the need for more theorisation, exploration and empirical research into formal woman-only networks and their benefits (Villeseche & Josserand, 2017, p. 1008). Similarly, more research was called for into theories related to women in IT, with multiple studies reflecting a lack of theorisation (Gorbacheva et al., 2019, pp. 46, 48; Tari, Annabi, Iribe Ramirez, Beneteau, & Ballard, 2019, p. 3). A model was developed by bringing together multiple theories, resulting in a paper entitled “Can AI networks improve the inclusion of women in AI?”, which is currently under review.

The overarching contribution of this research was the development and testing of a model for women in AI networks that explains and analyses how networking contributes to the advancement and persistence of women in the AI field. Understanding this assists women, businesses, industry and policymakers on how networking can support women in the AI workforce, thereby providing impetus to reducing gender bias in AI algorithms. A paper based on the findings from Phase 2 is currently under review at the Aslib Journal of Information Management, while a paper resulting from Phase 3 is being finalised for submission to the journal Gender, Work & Organization.

1.12. Structure of the Thesis

This thesis started out as a PhD by publication, which still includes the traditional research stages in addition to publication of multiple papers. However, due to various internal and external delays, described in Chapter 5, the thesis was converted to a monograph. The thesis structure thus follows a traditional monograph format. The next chapter reviews the literature on AI, AI bias, women in AI, professional networks, and women in AI career development and persistence. Chapter 3 describes the methodology used for each research phase, from the paradigm driving the research to the detailed data collection and data analysis procedures used in each of the three

phases. Chapter 4 details the research findings, which are presented and discussed according to each phase of the study. Finally, Chapter 5 provides a synthesised discussion of the entire study, organised per research objective. Contributions and recommendations are also provided in this closing chapter.

1.13. Conclusion

This research aims to address the issue of bias in artificial intelligence and the importance of increasing women's participation in AI development teams through an investigation of the role of WAINs in supporting women in AI careers. The study is structured into three phases and followed all ethical guidelines in producing findings and recommendations on how career persistence and advancement of women in AI can be supported by formal, professional networks. The next chapter reviews the current state of research on the topic and shows the development of the conceptual framework.

Chapter 2. REVIEW OF RELATED LITERATURE, THEORETICAL FOUNDATIONS AND DEVELOPMENT OF THE CONCEPTUAL FRAMEWORK

Although there is considerable previous research on the lack of women in technology in general and the problems this causes (e.g. Annabi & Tari, 2018, p. 5146; Branson, 2018, p. 5; West et al., 2019, p. 5) - for instance, for business competitiveness - there is little research into women in technology networks, particularly formal networks (Annabi & Tari, 2018, p. 5149) explicitly supporting women in AI. Further, it is unknown which attributes and features of these networks best support women in AI, especially related to their decisions to remain in the field and, more importantly, advance their careers in AI. There has been a call for further research into the impact of women in technology networks, and research into the barriers and interventions to improve inclusivity, and to focus on non-technical factors in AI bias (Annabi & Tari, 2018, p. 5152; Gorbacheva et al., 2019, p. 46; Obukhova & Kleinbaum, 2022, p. 206; Wanigasekara, Ali, French, & Baker, 2022, p. 31; West et al., 2019, p. 18).

The literature review begins with a discussion of AI, including sections on algorithms, algorithmic bias and gender bias in AI. Next is a review of previous research into women in technology, women in AI and the lack of, and importance of, diversity in AI. The following section reviews network research, including the types of networks and networking behaviour. Specific emphasis is placed on research conducted into women only and technology networks, which concludes with women in AI networks to establish the research gap.

2.1. Artificial Intelligence (AI)

Artificial intelligence is a broad term encompassing many different fields. The OCED offers a comprehensive definition: “An AI system is a machine-based system that can, for a given set of human-defined objectives, make predictions, recommendations, or decisions influencing real or virtual environments. AI systems are designed to operate with varying levels of autonomy” (Krafft, Young, Katell, Huang, & Bugingo, 2020, p. 6).

2.1.1. AI and the role of algorithms

Algorithms discover patterns in large datasets from which they learn rules for automated predictions (Bucher, 2018, p. 24). "An algorithm is a formally specified sequence of logical operations that provides step-by-step instructions for computers to act on data and thus automate decisions. Algorithms play a role in both automating the discovery of useful patterns in data sets and automating decision-making that relies on these discoveries. In simpler terms, it is 'a set of rules a computer follows to solve a problem" (Kochi, 2018, p. 16). Algorithms offer some of the most useful business cases for AI (Bharadiya, Thomas, & Ahmed, 2023, p. 87; Kochi, 2018, p. 16), such as natural language processing and image recognition used in a multitude of industries (Akerkar, 2019, p. 21; Bharadiya et al., 2023, p. 90; Bucher, 2018, p. 29).

Algorithms are critical to a subset of AI called machine learning, which is used in industries as diverse as education, finance, marketing, transport and security (Akerkar, 2019, p. 21; Bharadiya et al., 2023, p. 88; Bucher, 2018, p. 29). "Machine learning is a series of mathematical manipulations performed on important data to gain valuable insights. It is the study of algorithms that learn from examples and experience instead of hardcoded rules" (Akerkar, 2019, p. 11).

Learning algorithms can improve over time by using previous input-output relationships to predict new outputs without human intervention (Bucher, 2018, p. 24). These algorithms make predictions without having to be reprogrammed when presented with new data (Akerkar, 2019, p. 12). With big data and increasingly complex patterns in data, more autonomy is expected in these algorithms (Osoba & Welser, 2017, p. 17). Technical progress in areas such as storage capacity, processing power, big data and breakthroughs in predictive algorithms (OECD, 2019, p. 21) have raised the profile of AI as a technology that will impact most areas of business and society (Akerkar, 2019, p. 6; Bharadiya et al., 2023, p. 97).

Deep learning is the term used to denote sophisticated multi-level neural networks (OECD, 2019, p. 28) and represents some of the most valuable applications of AI to business, being more scalable and independent (Bharadiya et al., 2023, p. 87). However, problems arise related to the complexity and lack of transparency and explainability of solutions generated by these algorithms (Kochi, 2018, p. 4). Recent

breakthroughs in generative AI and large language models have accelerated the adoption of AI and seen its practical use pervade many sectors of business and society (Zhuo et al., 2023, p. 1). However, this has raised ethical concerns, particularly about biased, stereotyped or discriminatory outcomes (Zhuo et al., 2023, p. 2).

2.1.2. Bias in AI

Algorithmic bias refers to unfair discrimination against gender, race and other groups (Schwartz et al., 2022, p. 3; Springer, Garcia-Gathright, & Cramer, 2018, p. 450). Unfair AI has long term, real world detrimental implications for society (Bohdal, Hospedales, Torr, & Barez, 2023, p. 1) Bias in AI is related to stereotypes that machine learning algorithms learn from the data and biases inherent in language and society (Caliskan, Bryson, & Narayanan, 2017, p. 193; O'Connor & Liu, 2023, p. 2). An example is Google's photo app algorithm which was retracted when it was found to produce racist labelling of photographs (Bucher, 2018, p. 27). Bias can creep into AI solutions in multiple ways, including discrimination in training data sets and in machine learning models (Kochi, 2018, p. 4; Nadeem et al., 2022, p. 7). Training data is "Data that is used as an input to a machine learning algorithm in the process of populating (a.k.a. training) the machine learning model such that the trained model represents the patterns contained in the training data" (Kochi, 2018, p. 16).

A taxonomy of algorithmic bias was developed by Danks and London (2017, p. 4691), showing causes of bias are: 1) training data bias, which, being collected from the real world, contains biases built into society; 2) algorithmic focus bias, where some data is not included as it is not believed to be appropriate for the algorithm; and 3) processing algorithmic bias, which arises when conscious decisions are made in the processing in an attempt to negate other forms of bias, meaning the algorithm is no longer neutral, 4) transfer context bias, where the algorithm is used in a different context from which it was intended and developed for, and 5) interpretation bias, arising from the way the output of the algorithm is used and understood. Springer et al. (2018, p. 451) contend that all the disparate literature around classifying bias in algorithms can be consolidated as three sources of potential bias: from input data, computation, or outcome bias.

Osoba and Welser (2017, p. 17) and (Raza, 2022, p. 185) suggest that human biases built into data that the algorithms learn from will be mirrored in the inferences made by

the models used by the algorithms. Since algorithms are designed to discriminate in that they sort, classify and make inferences about data (Veale & Binns, 2017, p. 2), biases in historical data and machine learning models become part of the solution (Alzubaidi et al., 2023, p. 14; Kochi, 2018, p. 4). However, how the algorithms come to the answers they do in these cases is often opaque, not explainable and proprietary (Alzubaidi et al., 2023, p. 14; Burrell, 2016, p. 1). These problems will become more pressing with increasingly complex patterns in data, sophisticated multi-level neural networks and more autonomy in algorithms (O'Connor & Liu, 2023, p. 6; Osoba & Welser, 2017, p. 17).

Socially acceptable inferences can be programmed in to ensure fairness, but this will conflict with the accuracy requirements of algorithm outputs; additionally social acceptability is a complex and nuanced concept (Alzubaidi et al., 2023, p. 15; Osoba & Welser, 2017, p. 18). Further problems arise from mitigation techniques, for example with models used in algorithms being able to implement all the measures of fairness simultaneously (O'Connor & Liu, 2023, p. 5; Veale & Binns, 2017, p. 3). Subjective human involvement plays a role in selecting features and models used in the algorithms and how they include identifiable factors, such as race and gender (O'Connor & Liu, 2023, p. 11; Veale & Binns, 2017, p. 2). Ethical considerations are therefore necessary, including fairness. The pervasiveness of AI in all areas of life explains the multi-disciplinary interest in the issue of AI fairness (Alzubaidi et al., 2023, p. 11; Baleis, Keller, Starke, & Marcinkowski, 2019, p. 2). To be fair, AI systems should either not include identifiable factors, such as race and gender, or acknowledge group differences but explicitly treat the groups the same. In this way, stereotypes of the past will not be perpetuated in the solutions (Kochi, 2018, p. 6; OECD, 2019, p. 90). A concerted effort from business and society is needed in the form of company and public policy focusing on human-centred, ethical AI (Lainjo, 2023, p. 4966; OECD, 2019, p. 16).

Baleis et al. (2019) conducted a systematic review of perceptions of fairness in AI, which included some elements of AI bias but focused on people's cognitive and emotional responses to and perceptions of fairness in AI. Baleis et al. (2019) found people's perceptions of algorithmic fairness differed based on context and recommended further interdisciplinary research. Favaretto et al. (2019) focused on the discriminatory risks of data mining and associated biases and found human bias is a

barrier to fair AI systems. The study concluded that discrimination in data mining is significant yet often underestimated and that more research is needed into discriminatory practices in big data (Favaretto et al., 2019, p. 24). In a review by Alzubaidi et al. (2023, p. 2) algorithmic decision making and AI bias were examined, with a focus on trustworthiness. The recommendations from the review included the need for all stakeholders be involved, including developers and domain experts (Alzubaidi et al., 2023, p. 28).

2.1.3. Gender bias in AI algorithms

Stereotyping of women is found in all fields of AI, including robotics. Dufour and Ehrwein Nihan (2016, p. 7) replicated previous studies that showed perceptions of the ability of robots and acceptance of their role are grounded in gender stereotypes. Similarly, technology companies such as Apple and Microsoft have been criticised for giving their AI-based assistants a subservient female persona, perpetuating stereotypes that even extended to children (Feast, 2019, p. 1; O'Connor & Liu, 2023, p. 8; Raza, 2022, p. 196; Sirimanne, 2019, p. 1; UNESCO, 2019, p. 5). Further manifestations of bias have been found in legal, health, financial and news services (GAO, 2018, p. 7; Nemani et al., 2023, p. 2; O'Connor & Liu, 2023, p. 5; Raza, 2022, p. 196; UNESCO, 2019, p. 33). As evidence of the consequences of AI bias mounts, there have been calls to address the problem and hold the producers of AI applications accountable (Lainjo, 2023, p. 4973; Raji & Buolamwini, 2019, p. 429), especially because AI gender bias exacerbates and automates systemic discrimination (Lainjo, 2023, p. 4972; Raza, 2022, p. 196).

2.1.4. A socio-technical approach to algorithmic bias

Several technical approaches to identifying and reducing algorithmic bias have been proposed, including using statistical methods, audits of algorithms, automated reasoning and transparency and explainability requirements (Burrell, 2016, p. 10; Osoba & Welser, 2017, p. 22; Saka, 2020, p. 1; Veale & Binns, 2017, p. 3). Raza (2022, p. 186) and Osoba and Welser (2017, p. 24) recommends non-technical approaches, including user literacy and education, diversity in algorithm developers and algorithm regulation. Schwartz et al. (2022, p. 10) and Selbst et al. (2019, p. 14) argue that a socio-technical approach is required, given the complexity and context-specific nature of the issue. Draude et al. (2019, p. 325) developed a multi-disciplinary,

socio-technical framework presenting a socio-technical gender perspective consisting of data bias, technical model bias and emergent bias. Data bias is shaped by the society generating the data, which is fed into the algorithms. In contrast, technical bias arises from the models and features of the algorithm itself, and emergent bias stems from how the algorithm is used (Draude et al., 2019, p. 327). “Approaches proposed to mitigate discrimination in AI systems include awareness building; organisational diversity policies and practices; standards; technical solutions to detect and correct algorithmic bias; and self-regulatory or regulatory approaches” (OECD, 2019, p. 90). A technical focus fails to consider social factors, even extending to issues such as sustainability (Falk & van Wynsberghe, 2023, p. 8). Various social and cultural perspectives are thus important when reviewing the issue of gender bias, stemming from structural historical bias and stereotypes.

There is a gap in the literature to systematically review the social causes, consequences and solutions to gender bias in AI. This gap is filled in Phase 1 of this research and supports the first research objective: To conduct a systematic, interdisciplinary review of the current state of research on algorithmic gender bias.

2.2. Diversity in IT Development Teams

Despite evidence that more diverse technical teams result in higher employee performance and more innovative solutions (Barker, Mancha, & Ashcraft, 2014, p. 4; Gomez & Bernet, 2019, p. 390), IT still lacks diversity. The following sections review literature on gender diversity in IT.

2.2.1. Women in Information Technology (IT) teams

Attrition rates for professional women are highest for those in technology fields, especially in computing, with twice as many women leaving their jobs as men, and 56% leaving and moving to non-IT work within five years of starting (Annabi & Lebovitz, 2018, p. 1049; Ashcraft et al., 2016, p. 9; Roopaei et al., 2021, p. 497). Reasons for leaving include a poor working environment and a lack of promotional, sponsorship and networking opportunities (Nesaratnam et al., 2018, p. 155; Tokbaeva & Achtenhagen, 2023, p. 226). Similarly, there is little incentive to stay, with research showing organisational culture and implicitly biased workplaces can make career advancement difficult (Nesaratnam et al., 2018, p. 156; Tokbaeva & Achtenhagen,

2023, p. 226). Lack of leadership opportunities also causes women to leave the profession (Annabi & Lebovitz, 2018, p. 1052). Lower expectations of women in IT can end up harming future career growth and result in less risk-taking behaviour required in a competitive work environment (Nesaratnam et al., 2018, p. 156).

2.2.2. Women in AI

Women in the technology field account for 20-26% of the workforce (Armstrong et al., 2018, p. 1; Tokbaeva & Achtenhagen, 2023, p. 224), and the numbers for women in AI are even lower (Bello, Blowers, Schneegans, & Straza, 2021, p. 6; Kawamoto, 2019, p. 1). Furthermore, women only comprise 7.4% and 4.6% of the AI software and education workforce, respectively (McDonald, 2018, p. 1). The problem persists in research, with women authoring only 21% of papers at top AI conferences (Bello et al., 2021, p. 11). Further, only 20% of professorships in AI are held by women (Stathoulopoulos & Mateos-Garcia, 2019, p. 5) and, internationally, only 14% of AI researchers are women (Roopaei et al., 2021, p. 497). A study by the WEF (2018, p. 28) found a significant gender gap of 72%, which they suggest is particularly worrying given future predictions on the growth of AI as a career. Young (2021, p. 23) found structural inequality in the AI field, with women being more likely to have lower status and pay. This gender gap will likely persist as AI grows as a profession (Stathoulopoulos & Mateos-Garcia, 2019, p. 5; WEF, 2018, p. 32) presenting serious consequences requiring focused intervention (Roopaei et al., 2021, p. 502; Young, 2021, p. 22).

2.2.3. Barriers to women persisting in AI.

Traditional intra-company solutions to improve inclusivity in AI have been met with little success (Adams & Khomh, 2020, p. 104). For example, at Google and Facebook (now Meta), despite many self-reported initiatives to improve diversity, there is a predominance of white males in their technical workforce (West et al., 2019, p. 3; Young, 2021, p. 11). Some reports cite that women in AI research have found the field hostile, with female employees at Microsoft and Google staging protests (Corbett & Hill, 2015, p. 93; West et al., 2019, p. 5). Many of those leaving the profession in the technology field are female, often citing the masculine work culture (Roslyn, 2019, p. 49; Tokbaeva & Achtenhagen, 2023, p. 225). In fact research has shown that women

in computing are more likely to leave than those working in other professions (Roslyn, 2019, p. 46; Tokbaeva & Achtenhagen, 2023, p. 224). Studies cite pay and promotional opportunity disparity as reasons for leaving (Armstrong et al., 2018, p. 2; UNESCO, 2019, p. 25).

Generally, poor workplace conditions contribute to the lack of persistence in IT jobs, although interestingly, family responsibilities were not found to be a significant factor (Roslyn, 2019, p. 51; Tokbaeva & Achtenhagen, 2023, p. 224). Even in relatively equal societies such as Finland and Sweden, with progressive social inclusion policies, there is still a disparity in gender in IT occupations (Roslyn, 2019, p. 45; Tokbaeva & Achtenhagen, 2023, p. 227). This disparity is surprising given the general overall shortage of technology workers and the high number of women entering other scientific fields (Roslyn, 2019, p. 46). Interestingly, more equal societies and those considered as more developed countries tend to have more, rather than less, problems with gender parity (Adya, 2008, p. 602; Bello et al., 2021, p. 8). Mentorship and role models for female AI workers are lacking, and more valuable initiatives, such as sponsorship of women professionals, are even less prevalent in technology professions (Hewlett, 2014, p. 1; Tokbaeva & Achtenhagen, 2023, p. 227). Of particular relevance to this research, lack of networks is among the top three reasons for gender disparity in IT (Roslyn, 2019, p. 51; Tokbaeva & Achtenhagen, 2023, p. 227).

2.2.4. Solutions for more women in AI

Given the shortage of workers in the field, efforts should be directed at increasing the overall workforce (Roslyn, 2019, p. 48). Lack of use of informal networks by women in IT compared to men has been suggested as a reason for gender disparity, where women do not benefit from social capital effects that provide job opportunities and mobility (Gorbacheva et al., 2019, p. 49; Obukhova & Kleinbaum, 2022, p. 206). Some universities have instituted mentoring to improve the number of women entering technology fields, and research has proven mentorship is an effective strategy for retaining women in the IT workplace (Roslyn, 2019, p. 53). Sponsorship is one method employed to improve gender diversity, currently underused as a gender diversity tool (Roopaei et al., 2021, p. 499). Incentive-based practices to improve retention have also been recommended (West et al., 2019, p. 4). Training and continual learning have been cited as necessary to succeed in a technical career, but traditional training and

learning solutions put pressure on women in IT (Armstrong, Riemenschneider, Allen, & Reid, 2007, p. 150; Roopaei et al., 2021, p. 501; Tari et al., 2019, p. 3). Many large technology companies are trying to address diversity (Armstrong et al., 2018, p. 2; Shams et al., 2023, p. 2) through internal policies and industry consortiums.

2.2.5. Importance of gender diversity in AI development teams

Several researchers have suggested that gender diversity in the AI workforce can reduce machine learning bias and improve technical efficiency (Minevich, 2020, p. 1; Nadeem et al., 2022, p. 8) meaning there are performance benefits in addition to ethical and social benefits. Further, women must be integrated into the AI talent pool while the profession is in its infancy, as inclusivity will benefit AI applications and pay dividends to society (WEF, 2018, p. 32). Avila, Brandusescu, Freuler, and Thakur (2018, p. 3) propose that countries collaborate proactively with the private sector and publish guidelines to encourage gender diversity in AI development and research teams. Some companies have put policies in place to position women in management and higher-status jobs in the business (Shams et al., 2023, p. 2) . However, many diversity programs have been unsuccessful and can even paradoxically reduce diversity (Dobbin & Kalev, 2016, p. 52). The European Commission has stipulated that more inclusive development teams will assist in preventing bias and prevent possible exacerbation of gender discrimination beyond what is experienced in the physical world (UNESCO, 2019, p. 34). Communities that support women have been suggested as a potential solution (Wittemeyer, 2018, p. 65) with external networking providing the social capital necessary for career success (Wanigasekara et al., 2022, p. 29). Further, networks provide information and resources that can have positive work outcomes (Wanigasekara et al., 2022). However, only long-term and sustainable interventions are likely to be of benefit (Gorbacheva et al., 2019, p. 50).

Overall, more research on women's careers in AI, and what the reasons are for women not persisting and advancing in the AI profession is needed, with the imperative to find solutions to address the gender gap (Roopaei et al., 2021). Objective 3 of this research is to investigate women's career persistence and advancement in the AI profession.

2.3. Networking

Networks can be described in terms of their size, the strength of their members' ties to each other, the pattern of these ties or relationships and the benefits or resources for members (Porter et al., 2023, p. 9; Volmer & Wolff, 2018, p. 12). Networking is a broad construct, which the following section will review, including the types of networks, the stages, facilitators and outcomes of networking. The section culminates in networks designed for women in AI, as a potential support mechanism for women in the AI profession, which is at the heart of this research.

2.3.1. Types of networks

There are various types of networks, ranging from internal networks, limited to an organisation and its immediate business partners, to loose horizontal internal networks (Papafilippou, 2020, p. 1; Valkokari & Helander, 2007, p. 602). Formal networks have an official structure and identifiable public membership, providing instrumental and professional support (Emmerik, Euwema, Geschiere, & Schouten, 2006, p. 57; Porter et al., 2023, p. 14). The networks considered in this research are formal professional networks outside of organisational boundaries. The rise in the number and popularity of networks is not supported by similar levels of research (Gibson, Hardy III, & Buckley, 2014, p. 157).

2.3.2. Professional networks

Professional networking involves establishing and sustaining connections with others who can help with professional growth (Baumann & Utz, 2021, p. 1). Wanigasekara et al. (2022, p. 5) suggest that a distinction between informal, internal networking and internal professional networks is necessary. Professional networks improve their members' work and career success (Volmer & Wolff, 2018, p. 2; Wanigasekara et al., 2022, p. 8). Porter et al. (2023, p. 10) distinguish between instrumental and expressive networks, where the former offers job-related resources, and the latter offers affect and social support. Both types of networks will influence work attitudes, with instrumental networks being more important for members in finding alternative opportunities in the profession (Porter et al., 2023, p. 14).

2.3.3. Networking stages

Networking is an interpersonal, multidimensional, multifaceted construct that

encompasses building, maintaining and leveraging behaviour, which is goal-focused, with multiple informal contacts (Volmer, Orth, & Wolff, 2018, p. 680). Members of networks typically go through several stages of involvement in their network, from initiation to growth and then usage (Porter, Woo, & Campion, 2016, p. 4). Rajagopal, Joosten-ten Brinke, Van Bruggen, and Sloep (2012, p. 1) propose a similar sequence from a connection viewpoint, which they termed building, maintaining and activating. Wolff and Spurk (2020, p. 277) provide a similar sequence starting with network building behaviour, where new contacts are made. Next is network maintaining behaviour, where connections are maintained and developed, followed by network leveraging behaviour where contacts are used for instrumental support and resources. Instrumental resources are job-related, including "information, expertise, professional advice, political access, influence, or material resources" (Porter et al., 2023, p. 10). This type of behaviour could be expected by women in AI networks and links to the overall research problem of how networks can support women in AI.

2.3.4. Facilitators of networking

Personality traits such as members being agreeable, extroverted and open to experiences facilitate successful networking behaviour, although not always in external networks (Wolff & Kim, 2012, p. 60; Wolff, Weikamp, & Batinic, 2018, p. 2). Forret (2014, p. 8) describes extraversion (self-esteem and friendliness), openness to new experiences (flexibility, pro-active), consciousness (motivation and ambition), and agreeableness (trusting and cooperative) as being positively related to networking, with extroversion and openness being the best predictors. Bensaou, Galunic, and Jonczyk-Sédès (2014, p. 31) cite self-esteem, self-monitoring, self-confidence and extraversion as predictors of networking behaviour. Determinants of networking behaviour have also been researched from a motive perspective, with the need for achievement being more of a powerful motivator than social needs (Wolff et al., 2018, p. 10). Carboni, Cross, Page, and Parker (2019, p. 13) suggest that 'energisers' succeed in networking due to their enthusiasm, performance in the network, ability to energise others and build a sense of trust.

2.3.5. Outcomes of networking

Baumann and Utz (2021, p. 1) provide evidence of objective and subjective benefits of networking, including access to knowledge and job search and work assistance. Gibson et al. (2014, p. 156) suggest that access to information and social capital

arising from networking will lead to career success. Access to information has broad-reaching benefits, including cutting-edge industry knowledge, information about job openings and career insights (Gibson et al., 2014, p. 156). Additionally, networking, especially internal networking, can be considered a career-enhancing strategy (Wolff & Kim, 2012, p. 45). An interesting suggestion from longitudinal research and more recent research is that social capital facilitates networking and career success (Wanigasekara et al., 2022, p. 6; Wolff & Moser, 2009, p. 204). Porter et al. (2023, p. 10) found that employee networks can increase job satisfaction and organisational commitment and reduce turnover.

Important for the context of this research into women in AI, is that there are career advantages of networking, including increased job satisfaction, mobility and career visibility and recognition (Cross & Armstrong, 2008, p. 602; Wanberg, van Hooft, Liu, & Csillag, 2020, p. 4). Fryczyńska and Ivanova (2019, p. 213) hypothesised that increasing networking behaviour would assist with career advancements, either within an organisation or to change to a better job. However, most of this previous research linking networks and career success has focused on internal organisational or informal networks, which are different in nature and scope to the type of formal networks for women that this research is concerned with. Networks assist members in job search and change, improving career competencies (Forret, 2014, p. 2; Wanberg et al., 2020, p. 6). Networks provide social capital through contacts and human capital through skills, positively impacting career advancement in organisations (Wanigasekara et al., 2022, p. 6).

2.3.6. Women-only networks (WONs)

Weis and Lay (2019, p. 184) and Bapna and Funk (2021, p. 594) determined that women gain fewer career benefits from networks than men do, and this can have a moderating effect on promotions and compensation of women. There is little research on female networking behaviour (Gremmen, Akkerman, & Benschop, 2013, p. 299; Woodwark, Wood, & Schnarr, 2021, p. 440); however, the consensus is that women have less access to networks that support their careers than men do (Weis & Lay, 2019, p. 174). Women-only networks (WONs) usually have a smaller membership which tends to make the networks less powerful when it comes to influencing career success (Carboni et al., 2019, p. 3). Women tend to leverage networks less than their male counterparts which can translate into lower pay (O'Neil, Hopkins, & Sullivan,

2011, p. 736; Weis & Lay, 2019, p. 185), and experience more barriers to networking than men (Carboni et al., 2019, p. 43). In one of the few studies into formal professional WONs, large-scale, mixed-method research spanning 30 organisations found that these networks encouraged efficient collaboration and exposure to new opportunities and viewpoints (Carboni et al., 2019, p. 27). In a small study of French entrepreneurial female networks, Bourdil and Géraudel (2016, p. 275) found that strong ties among members improved network satisfaction. However recently (Woehler, Cullen-Lester, Porter, & Frear, 2021, p. 228) stated that more research is needed on WONs and their impact on career success for women.

There are various types of WONs. The first distinction is between informal and formal WONs (Durbin, 2011, p. 94). Informal WONs tend to be more social and made of friends and family, while formal WONs are created for professional or occupational purposes (Durbin, 2011, p. 99; Villeseche & Josserand, 2017, p. 1007). The second distinction is between internal, intra-organisational and external or inter-organisational networks (Wanigasekara et al., 2022, p. 47). However, there is no research that has positioned WONs that can be used for this research on WAINs, therefore the framework in Figure 2 is presented to distinguish between the types of WONs.

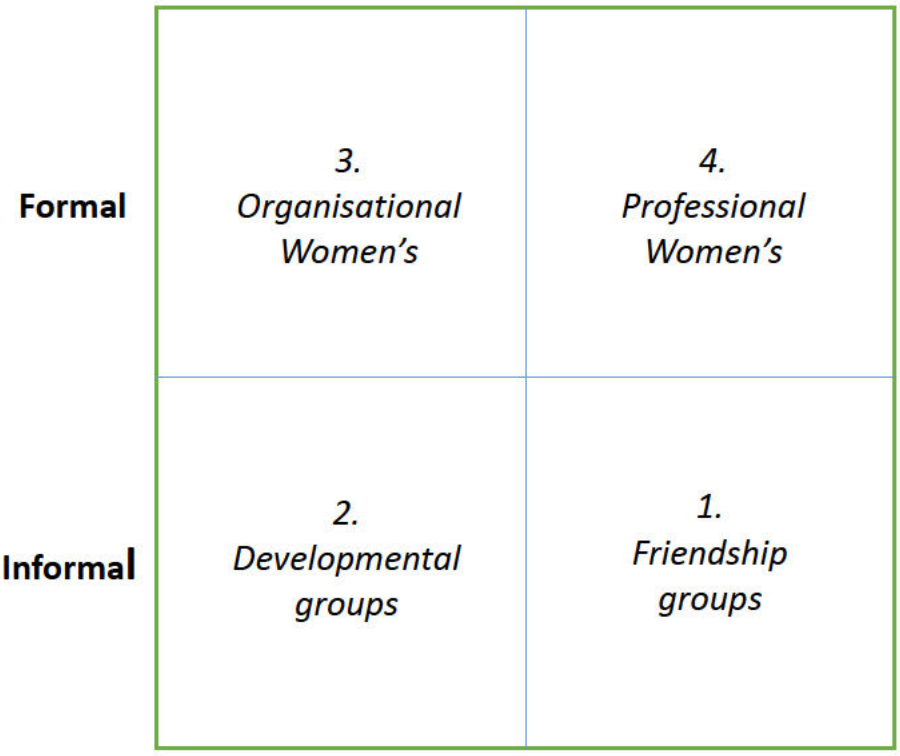

Figure 2 Network types (Dobrow & Higgins, 2005; Porter, Woo, Alonso, & Snyder, 2023; Villeseche & Josserand, 2017)

Quadrant 1 represents friendship groups, which is the equivalent of “the old boys club” typically found in male networks, which offers little contribution to women’s professional lives, as women tend to be less skilled at gaining social capital from friendship networks (Durbin, 2011, p. 97). Quadrant 2 is developmental groups which are arranged internally to support the progression of women from within the company, often in the form of informal mentorship groups. Both quadrants 1 and 2 are informal networks. Cross and Armstrong (2008, p. 603) found that informal networks are critical to women’s career advancements; however, this is in contrast to a more recent review of research into the topic by Villeseche and Josserand (2017, p. 1007), who found several limitations to informal networks when it comes to professional advancement.

Quadrant 3 represents formal and official networks created within organisational boundaries. These networks are often created in recognition of diversity problems, primarily due to the lack of women in managerial positions, and are usually found within larger organisations (Villeseche & Josserand, 2017, p. 1012). Although the most common type of formal WON, these have been criticised for being divisive (Durbin, 2011, p. 100) but can serve a strategic purpose for the organisation if managed well (Donnellon & Langowitz, 2009, p. 32). Several names are given to these networks, including employee or business resource groups, network groups and women affinity groups (Annabi & Tari, 2018, p. 5147). Donnellon and Langowitz (2009, p. 32) created a ‘mission pyramid’ of organisational women’s networks, with connection at the base of the pyramid and then graduating to support competency, career development, career advancement, and business development. Previous research has shown that Organisational WONs (quadrant 3) benefit the organisation the women work for through increased job commitment (Wanigasekara et al., 2022, p. 1) and that women benefit more from formal networks than men do (O'Neil et al., 2011, p. 741; Villeseche & Josserand, 2017, p. 1013).

The final quadrant is most applicable to WAINs. Quadrant 4 is professional formal women-only networks created outside of the place of employment that women belong to, irrespective of the size of the organisation they work for and their roles or seniority (Villeseche & Josserand, 2017, p. 1012). Not only is this quadrant an emerging area of research with the least available academic literature, but it also offers the potential

for more extensive benefits for women who belong to them (Villeseche & Josserand, 2017, p. 1008). Formal WONs are more beneficial to women than informal networks (Durbin, 2011, p. 93) and aid women in gaining strategic knowledge and access to resources (Villeseche & Josserand, 2017, p. 1024).

Academic literature on women-only networks has focused more on informal networks (quadrants 1 and 2), and what little research there has been on formal women-only networks has tended to focus on internal organisational networks (quadrant 3) (Villeseche & Josserand, 2017, p. 1008). Women join formal WONs for several reasons, including access to work opportunities, knowledge and skills; gaining professional and social contracts; career advice and support and helping and sharing with others (Bapna & Funk, 2021, p. 595; Durbin, 2011, p. 99). Macintosh and Krush (2014, p. 2630) and Porter et al. (2023, p. 16) hypothesised that professional networks would improve job satisfaction, particularly for females. There is a gap between the importance of these networks in business and research interest in the topic (Bourdil & Géraudel, 2016, p. 267). This view is corroborated in an extensive review of the literature on formal women-only networks by Villeseche and Josserand (2017, p. 1004), which shows that research on external, formal WONs is scarce.

2.3.7. Technology WONs

If there is little research into professional WONs, then there is even less into those specifically designed to support women in technology (Annabi & Tari, 2018, p. 5152). In the engineering profession, Papafilippou (2020, p. 5) explain that internal networks provide openness and the ability to express concerns with inequality in the workplace, while external networks enable women to “to build bridges with other organisations and professional bodies and influence policy”. One specific study in the technology sector determined that identity-based networking should be encouraged as a critical support tool for women in technology (Adya, 2008, p. 630). A paper by Gabbert and Meeker (2002, p. 65) described the role of three support communities and concluded that they provide beneficial support for women in computing. In a small Finnish study, Hyrynsalmi and Sutinen (2019, p. 5) explored the role of women in software communities, with a focus on attracting women to the profession, as opposed to this research aimed at career persistence and advancement. Finally, Bapna and Funk (2021, p. 2) found that women in IT experience both search (finding contacts) and social (interacting across social boundaries) barriers to networking, however this

research was more related to internal networks rather than external networks, such as those that this research is concerned with on Women in AI networks.

2.3.8. Women in AI networks

This research is specifically on professional WONs supporting women in AI, related to the problems resulting from a lack of diversity in AI development teams. Communities to support women in AI have arisen to inspire, promote and increase the number of women in AI (Cerit, Dindarian, & Cilo-van Norel, 2020, p. 1). Although there are many support communities, they are under-researched and under-theorised (Annabi & Tari, 2018, p. 5152; Gorbacheva et al., 2019, p. 46; West et al., 2019, p. 18).

This literature review has exposed research on the topics of AI gender bias, the lack of women in AI and need for solutions to increase gender diversity in development teams. Networks, as a potential support for women in their careers, were reviewed in depth with the women in AI networks positioned within the types of networks. Little existing research was found on these types of networks, and there is a gap in the literature as to how these networks support women in their AI careers. This links to the overall research problem and the research objectives about WAINs and the relationships between networking behaviour and career persistence and advancement for women in AI.

2.4. Conceptual Framework Development

Based on the review of the literature, no model was found that looks at women in AI networking and careers. This gap can be filled by conceptualising a new model, based on theories of Women in IT and a model of networking behaviour.

2.4.1. Theories related to lack of gender diversity in IT

The issue of discrimination against women in technology has been acknowledged for many decades, and under-theorisation is acknowledged (Gorbacheva et al., 2019, p. 43; Tassabehji, Harding, Lee, & Dominguez-Pery, 2020, p. 25). Early work had opposing views along the “nature versus nurture” spectrum, namely essentialism and social constructivist theory. Determinism or essentialism theory argues that structural

and biological differences between men and women are responsible for the lack of women in technology, with men being more biologically suited to careers in technology (Nesaratnam et al., 2018, p. 157; Tari et al., 2019, p. 3; Tassabehji et al., 2020, p. 5). According to this theory, the biological differences in genders make for better outcomes with mix-gender development teams, as women bring different skills and perspectives (Adya, 2008, p. 603). This argument forms part of the reasoning for this study as to why having women in an AI team would result in better outcomes; however, only because of different viewpoints and skill sets, not due to an inability to understand or complete technical tasks.

Essentialist theory suggests that women are incapable of similar productivity to their male counterparts and that this is fixed and predetermined (Adam, Howcroft, & Richardson, 2001, p. 341; Trauth & Quesenberry, 2007, p. 21). Several studies have discredited this and the implications of the view that interventions are unlikely to improve gender gaps (Adya, 2008, p. 603; Osunde, Bacon, & MacKinnon, 2014, p. 18). A UNESCO report on STEM reiterated these points in the 2030 sustainable development agenda (Chavatzia, 2017, p. 11). According to this view, gender would be a fixed variable, with women being biologically less able to perform in I.T., suggesting that male and female teams should be separate (Trauth, 2002, p. 100). A further criticism is that the theory fails to take context into account and is, therefore, too generalised (Trauth & Quesenberry, 2007, p. 22). An extensive review of research into gender imbalance in IT was conducted by Gorbacheva et al. (2019, p. 44), in which they established that essentialism was the predominant theory underpinning much research until recently but that it is simplistic and perpetuates inaccurate stereotypes. This review contradicts an earlier study of gender in IT papers, where the social constructivist perspective was prevalent (Gallivan, 2013, p. 51).

In contrast to essentialism, social constructivist theory suggests that the inherent biases against women in IT are culturally based, explained by societal and cultural stereotypical attitudes and beliefs surrounding technology and gender (Adya, 2008, p. 604; Osunde et al., 2014, p. 18; Trauth, 2006, p. 1155; Trauth & Quesenberry, 2007, p. 24). Discrepancies between genders in STEM are attributed to social and cultural norms and processes (Chavatzia, 2017, p. 12). Males are more socially conditioned to enter technical careers. At the same time, women are encouraged through societal influence to enter more social careers, placing jobs in IT in the male camp (Gorbacheva

et al., 2019, p. 44; Trauth & Quesenberry, 2007, p. 23). This theory infers that biased beliefs reduce confidence and motivation for women in IT careers (Osunde et al., 2014, p. 18). There are debates within this theory, with some suggesting women find mechanisms to better fit into the male world and others suggesting the masculine fields need to open up to accept more females (Trauth, 2002, p. 101). Although both the essentialist and social constructivist theories are diametrically opposite in their explanation, they are similar in their implications in that both theories imply gender is fixed and can be criticised as treating women as a single homogenous group (Trauth, 2002, p. 111; Trauth, Quesenberry, & Morgan, 2004, p. 116). This view is countered by the individual differences of Gender and IT theory (IDTGT).

2.4.2. Individual Differences Theory of Gender and IT (IDTGIT)

The IDTGIT theory was tested empirically over multiple sites from 2002 to 2006 (Trauth, 2006, p. 1155). Since then, numerous studies, some by the same author and some by others, have added credibility to the theory (Trauth & Quesenberry, 2005, p. 8). For example, Chavatzia (2017, p. 23) reports that female identity and individual working and family environments influence women's decisions to enter STEM careers. As the name of the theory suggests, it seeks to address the problem of lack of gender diversity in IT by treating women as individuals in the IT profession (Trauth, 2006, p. 1156), in contrast to other theories which concentrate on differences between the genders as groups (Trauth et al., 2004, p. 117). The strength of this theory is demonstrated in a review of research on gender and IT conducted by Gallivan (2013, p. 51), where many papers used the IDTGIT as a theoretical lens.

The theory is based on three constructs – environmental influence, individual identity and individual influence (Trauth, Quesenberry, & Yeo, 2005, p. 30). Environmental influence provides context for life and career influences, while individual identity includes demographic, lifestyle and professional characteristics and individual influence includes personal influences, which shape women's decisions to enter and persist in the IT profession (Trauth, 2006, p. 1156; Trauth, Cain, Joshi, Kvasny, & Booth, 2016, p. 22). These constructs together can be used to explain gender disparity in IT and have been tested in numerous studies (Annabi & Lebovitz, 2018, p. 1055). The theory can also uncover within gender variations, including minorities from the LGBT community and racial minorities (Kvasny, Trauth, & Morgan, 2009, p. 3; Trauth & Booth, 2013, p. 6).

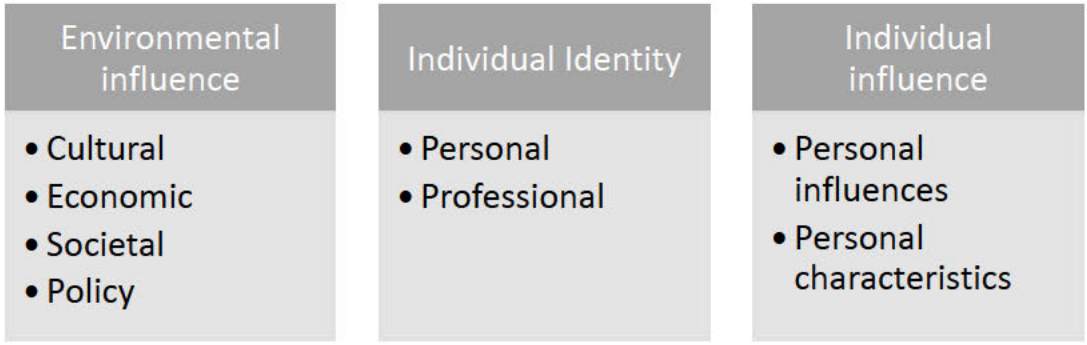

Figure 3 Trauth's IDTGIT constructs

The constructs from the IDTGIT theory of relevance for this research on women in AI are individual identity and individual influence. From individual identity, the concepts of gender and professional identity apply, since WAINs are networks for those who identify as women and members of the AI profession. Gender identity is multidimensional and should be measured in a way that prevents labelling, misgendering and stereotyping (Ho & Mussap, 2019, p. 217; Schulenberg et al., 2023, p. 179). Additionally, intersectionality is an important dimension, with gender-ethnic intersectionality a critical element of diversity in IT (Buolamwini & Gebru, 2018, p. 79; Raza, 2022, p. 197). Professional Identity includes how attitudes, beliefs, experiences and motives shape one's career and professional role (Dobrow & Higgins, 2005, p. 569; Greer & Kirk, 2022, p. 7) and can be applied to AI professional identity. Brooks, Hardgrave, O'Leary-Kelly, McKinney, and Wilson (2015) measured attachment to the IT profession in their study on IT professionals and retention.

Individual influence, specifically personal influence, is the other construct from the IDTGIT theory of relevance to this research. Personal influences include people, such as role models and mentors, and educational experiences. Education includes learning and career support opportunities (Trauth et al., 2016, p. 22), which in WAINs range from education on AI issues and technology, to career and personal development, to learning about job opportunities and research. The large, publicly available WAINs offer numerous opportunities for members such as short courses, events and hackathons. Thus, learning opportunities, mentorship and role models, and gender and professional identity are elements that influence differences within gender in IT.

Lack of female mentors, role models and networks have been cited as the top three reasons for gender disparity in IT (Roslyn, 2019, p. 51). WAINs offer formal mentoring programs and, through ambassador and leadership positions, can inspire members by being role models (Roopaei et al., 2021, p. 498). In research into barriers facing women in IT, Annabi and Lebovitz (2018, p. 1060) found that lack of networks, role models and mentors were significant barriers and proposed further research into barriers to career persistence. Additionally, more research on networking and career mentoring and how professional networks can assist women in IT was proposed by Armstrong et al. (2018, p. 20). Another theory seeking to explain women in IT careers is Ahuja's stage model of barriers facing women in AI, which is also used in the development of the conceptual model.

2.4.3. Ahuja's stage model of barriers facing women in IT

In a seminal paper in 2002, Ahuja conceptualised several factors that combine both determinism and social theories and considered factors that impact three separate career stages of women in technology – entering the field, persisting in the field and advancing in the field (Ahuja, 2002, p. 22). This well-cited study intended to identify leakages from the women in the IT pipeline. The first stage is entry into the IT field, which includes the choice of IT as a career and entry-level jobs. The second stage of career persistence is the likelihood of leaving the profession, either for a job in a different field or leaving the workforce altogether. The final stage of career advancement relates to promotion, increase in professional status and salary. Ahuja (2002, p. 22) proposed two major sets of factors influencing each career stage: social and structural. Social factors are those cultural factors that women hold internally and those presented externally in society. An example of the former is self-expectation resulting in self-selection of non-technical careers, and examples of the latter are stereotypes about women in IT. Structural factors relate to those inherent in the nature of the profession and the structure of organisations (Ahuja, 2002, p. 25). At a more granular level, Ahuja considered social expectations and work-family conflict as the primary social factors, where social expectations shape women's self-confidence and performance in computing.

In contrast, work-family conflict suggests a constant push and pull between long demanding hours in IT and the demands of family life, including the mother as the primary caregiver (Ahuja, 2002, p. 25). Lack of informal networks within organisations

to support women in the profession Ahuja (2002, p. 28) also considers a social factor. However, this lack of access can be detrimental when gaining information and building relationships necessary to succeed. The structural factors considered in this model are occupational culture, which is predominantly masculine with long working hours, and a lack of role models and mentorship, whose success can be modelled. Organisational structure is another structural factor, with poor representation on corporate boards and senior executive positions. Internal mentorship is another structural factor related to informal networks and often reciprocal. The social and structural elements interact and can compound each other in terms of how they exacerbate barriers for women in IT (Ahuja, 2002, p. 26).

Ahuja's model informs this research by providing an empirically tested set of constructs to measure women in IT careers. The three stages in women in IT careers are entry, persistence and advancement. Only the stages of career persistence and advancement were included in this study on women in AI, as these stages are related to networking which is what the research problem concerns. Excluding the career entry stage is similar to research by Armstrong et al. (2018, p. 13), who extended the Ahuja model, also focusing on the persistence and advancement career stages. They created an expanded, updated, empirically validated model from Ahuja's work (Armstrong et al., 2018, p. 2). The relationships they found confirmed that informal networks help advance women's careers in IT. They proposed that a future avenue of research should be around networking, psycho-social and career mentoring, and how professional networks can assist women in IT (Armstrong et al., 2018, p. 20).

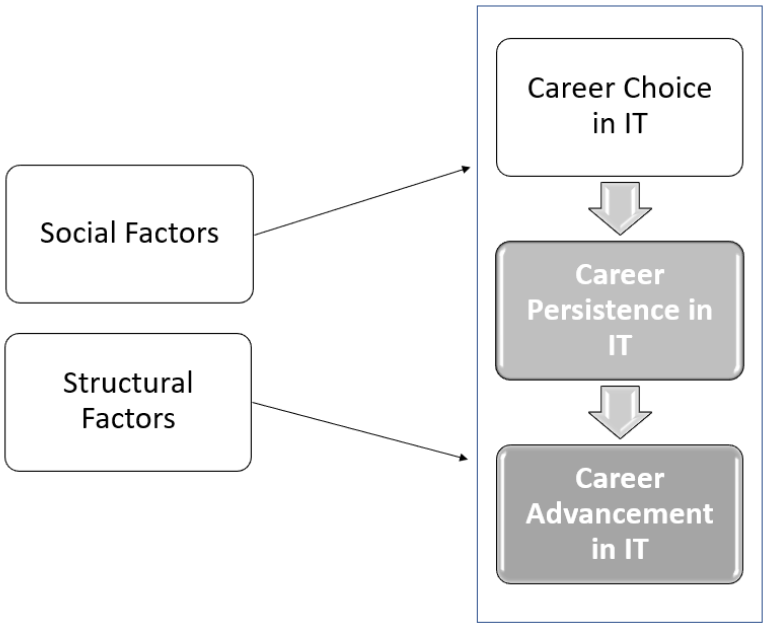

Figure 4 Ahuja's stage model constructs (Ahuja, 2002, p. 22)

Career persistence is staying in IT rather than leaving for another profession or leaving the workforce altogether, while career advancement relates to improving one's position in IT through promotion, status or salary (Armstrong et al., 2018, p. 15). In Ahuja's model, social expectations, work-family conflict, lack of supportive work culture and role models affect career persistence (Armstrong et al., 2018, p. 6). In contrast, informal networks, lack of mentors and organisational structures affect career advancement (Armstrong et al., 2018, p. 5). However, the social and structural factors are related to the women themselves or the organisation they work for and therefore do not consider external networks such as WAINs. Thus the model and research are insufficient when considering external professional networks, which is the focus of this research.

Thus Ahuja's model and the IDGIT theory together provide useful perspectives on networking and women's career advancement and persistence. Particularly, individual identity and personal influences, from IDTGIT theory and the career constructs from Ahuja's model can be combined, allowing focus on the career aspects of women in IT. The complexity implied by theories considering the lack of diversity in women in the IT profession means that more theory and more robust theory is relevant (Trauth & Quesenberry, 2007, p. 30). One additional construct is needed to complete the initial conceptual model for this study – networking behaviour.

2.4.4. Wolff's model of networking behaviour

Networking behaviour is building, maintaining and leveraging professional relationships that benefit the creation of information, support and contacts to empower the professional success of network members (Wolff & Spurk, 2020, p. 277). Other attempts at explaining networking behaviour have not been aimed at employed professionals or are not multi-dimensional and therefore lack the nuances required for this study. Wolff's model suggests networking behaviour can be broken down into three constructs: building, maintaining and leveraging behaviour, which can be further distinguished as being internal or external (Wolff & Spurk, 2020, p. 281; Wolff et al., 2018, p. 3). *Network building behaviour* involves creating new contacts within the network, which requires social skills and member ability to connect, based on participation levels and how active members are. *Network maintaining behaviour* involves maintaining and developing contacts through socialisation and personalised exchange of intangible resources based on trust. *Network leveraging behaviour* means actively using contacts in the network for instrumental support and resources to gain expertise, job insights and professional advice from other members (Wolff & Spurk, 2020, p. 281).

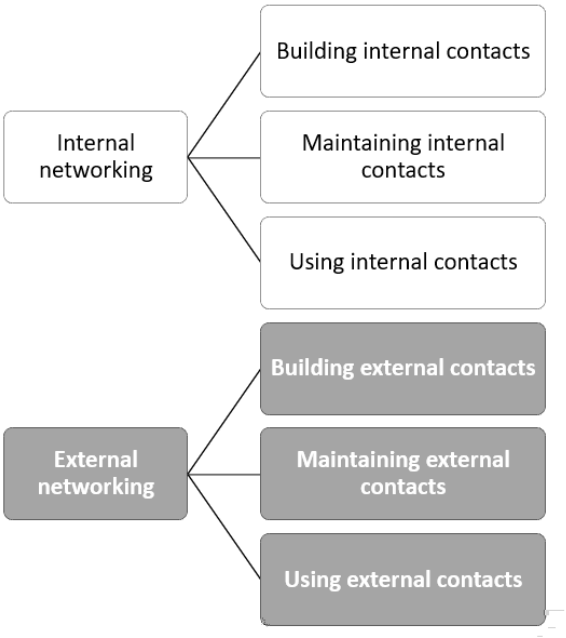

Figure 5 Wolff's networking behaviour constructs (Wolff & Spurk, 2020, p. 281).

Only external networking behaviour is relevant to the development of the conceptual model, as WAINs are by nature external to an organisation. Fryczyńska and Ivanova (2019, p. 209) suggest that increasing networking behaviour assists with career

advancements, which supports the linking of constructs in the conceptual model, to be discussed next.

2.4.5. The Conceptual model

An initial conceptual model for the study was developed based on the above theoretical foundation. The model was based on constructs from three established theories: Trauth's Individual differences theory of gender in IT (Trauth et al., 2004), Ahuja's stage model of barriers facing women in IT (Ahuja, 2002), and Wolff's networking behaviour (Wolff, Moser, & Grau, 2008).

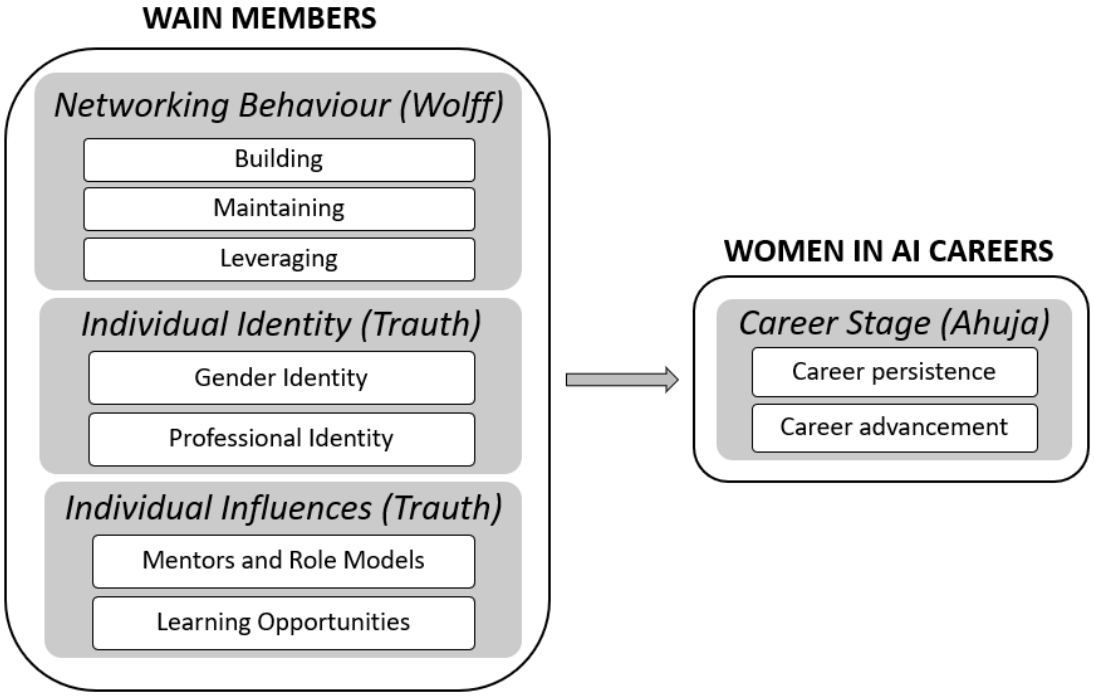

Figure 6 Initial conceptual model constructs

The initial model thus provides a theoretical contribution by linking elements from the theories from which several relationships can be proposed. Networking behaviour is the independent variable, while the career stages of persistence and advancement are the dependent variables. Mentorship and roles models, and learning opportunities are individual influences that mediate the relationship between networking behaviour and the career stages. Mediators are variables that intervene between the independent and dependant variables (Wu & Zumbo, 2008, p. 369). Gender and AI professional identity moderate the relationship between networking behaviours and career

persistence and advancement. Moderators are variables that strengthen the relationship between dependent and independent variables (Wu & Zumbo, 2008, p. 370). These relationships between networking and careers are presented in Figure 7.

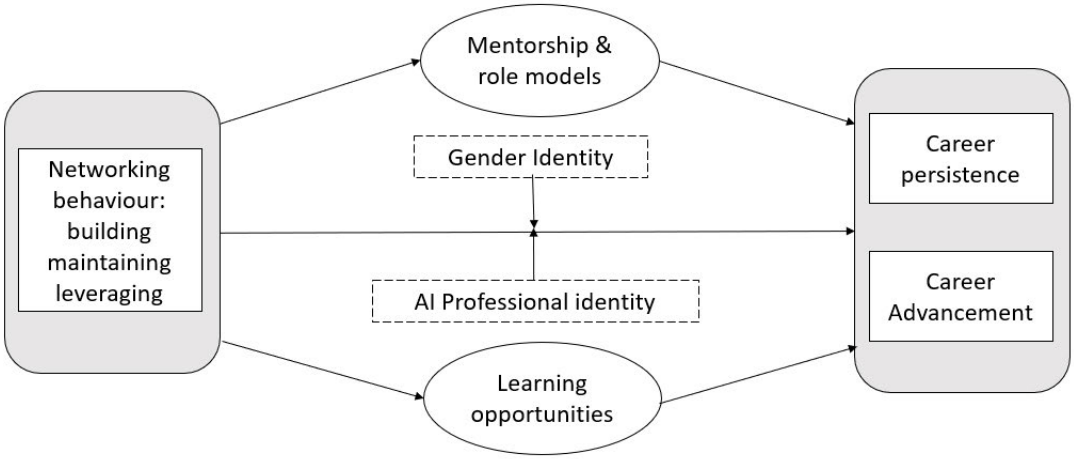

Figure 7 Initial conceptual model.

Women in AI careers

Career persistence refers to WAIN members staying in the AI profession and not planning to leave their current AI job. A positive association is indicated through commitment to the AI profession, similar to commitment to the IT profession (Brooks et al., 2015, p. 9). *Career advancement:* For women in AI to make a difference in AI development teams, they need to not only stay in the profession but also advance into higher-level positions and attain their career goals. Greer and Kirk (2022, p. 3) explain that this upward career mobility has barriers related to the gender gap, identity and a lack of mentors and role models.

WAIN member networking behaviour

Networking behaviour is based on Wolff's (2018) model and comprises network building, maintaining and leveraging behaviour. Network building involves establishing new contacts in the network, while network maintaining behaviour involves developing contacts and network leveraging involves actively using the connections made (Kim, 2013, pp. 123, 132; Wolff & Kim, 2012, p. 47). How active members are, for example, in attending network events and maintaining connections with other members, would be relevant here.

The direct relationship between networking behaviour and career persistence and advancement for women in AI is shown in Figure 7, and is captured in the following propositions:

- The more networking behaviour displayed by WAIN members, the stronger their career persistence.
- The more networking behaviour displayed by WAIN members, the stronger their career advancement.

Women in AI individual identity and influences

Individual identity and influences are based on the IDGIT theory. Individual identify includes gender and professional identity, as mediators, seen in Figure 7. *Gender identity* is important as WAINs are designed for women and are inclusive and supportive of gender minorities (Roopaei et al., 2021, p. 499). *AI professional identity* relates to how WAIN members view their interaction with the AI profession as essential to their sense of self (Brooks et al., 2015, p. 9). Individual influences include influence from people in the form of mentors and role models and from the opportunities and resources in the form of learning opportunities, which are provided by the network and mediate the relationship to the AI careers . *Mentors and role models:* The large, publicly available WAINs have strong formal and informal mentorship programs and showcase role models through awards and publicity (Roopaei et al., 2021, p. 498). *Learning Opportunities:* this broad concept includes career and educational opportunities and other essential career resources (Hirschi, Nagy, Baumeler, Johnston, & Spurk, 2018). In WAINs, this ranges from learning about job opportunities, new skills, knowledge, events and even speaking opportunities. The research propositions arising from individual influences, as shown in Figure 7, are:

- *Gender identity* moderates the relationship between networking behaviour of WAIN members and their AI career persistence and advancement.
- AI *professional identity* moderates the relationship between network behaviour of WAIN members and their AI career persistence and advancement.
- Support from WAIN *Mentors and role models* mediates the relationship between networking behaviour and their AI career persistence and advancement.
- WAIN *learning opportunities* take-up mediates the relationship between WAIN member networking behaviour and their AI career persistence and advancement.

Overall, the conceptual model depicts that network behaviour, when combined with the network's influences on its members and the individual identity of members, is proposed to provide the support needed to ensure women in AI careers persist and advance, thereby increasing gender diversity in AI. Due to the paucity of literature and previous research, the theoretical lens and literature used to develop the model lacked application to AI. Thus, the conceptual model and the propositions needed confirmation and fine-tuning by WAIN experts in Phase 2. The conceptual model provided the first step in meeting the overall research purpose of determining how women in AI networks support women in persisting and advancing in the AI field and to develop and test a theoretically sound model that links networking behaviour and usage to women in AI career persistence and advancement.

2.5. Conclusion

The literature review has detailed the complexity of networking and revealed the gap in the literature related to formal WONs designed for the AI profession. Further, the review shows the current state of research on women in AI careers, exposing the lack of previous research on gender bias in the context of women in artificial intelligence networks (WAINs). The initial conceptual model development followed an integrative, critical review approach, which aimed to evaluate, synthesise and reconceptualise in pursuit of developing a suitable framework (Snyder, 2019, p. 335). The result was a set of propositions that address the research gap. Firstly, the more women in AI networks engage in networking behaviour, the more likely they are to persist and advance in their careers. This relationship is supported in literature, although not specifically for women in AI (e.g. Forret, 2014; Fryczyńska & Ivanova, 2019; Volmer & Wolff, 2018). Secondly, gender and professional identity moderate the relationship between WAIN members' networking behaviour and their AI career persistence and advancement. Although not explicitly tested in previous research, literature does show that professional identity can strengthen career satisfaction and commitment (Brooks et al., 2015, p. 18). Finally, the initial model proposed that learning opportunities and support from network mentors and role models mediate the relationship between networking behaviour and women in AI career persistence and advancement. Hirschi et al. (2018, p. 20) highlighted the importance of such opportunities and resources for careers. Overall, the conceptual model supports Objective 2 of the research which was

to develop a model of women in AI networking and career persistence and advancement. How the model is refined and tested is explained in the next chapter: Research methodology.

Chapter 3. RESEARCH METHODOLOGY

3.1. Introduction

The literature review in Chapter 2 provided insight into previous research on AI bias, women in AI and networking. This chapter explains the methodology for each phase of the study, including how the data analysis from each phase feeds into the next stage. The specific research problem, objectives and, where applicable, the research philosophy and design are addressed for each phase.

3.2. Statement of the Problem

In summary, the extent to which women in AI networks (WAINs) can assist women in persisting and advancing in the AI field is worth investigating given the importance to the future of women not just in AI but whose lives will be affected by all the fields AI is, and will be, applied to (Lainjo, 2023, p. 4966; West et al., 2019, p. 15). Currently, how WAINs support women in AI careers is unknown. Therefore, this research aimed to determine the extent to which women in AI networks support women in advancing and persisting in the AI field and to develop and test a model that links network usage to women in AI career persistence and advancement.

3.3. Research Objectives

The overall objectives per Chapter 1 were:

1. To conduct a systematic, interdisciplinary review of the current state of research on algorithmic gender bias.
2. To develop a model of women in AI networking and career persistence and advancement.
3. To investigate women's career persistence and advancement in the AI profession.
4. To examine networking behaviour of women in the AI profession.
5. To explore Women in AI Network (WAIN) benefits and resources.
6. To determine the relationships between networking behaviour and career persistence and advancement.

The approach to achieve these objectives follows.

3.4. Three-Phase Research Process

The three phases of the research were introduced in Chapter 1, summarising the design as multi-phase exploratory sequential (Ivankava et al., 2007, p. 265). The results of each stage feed into the next step (Creswell, 2009, p. 208).

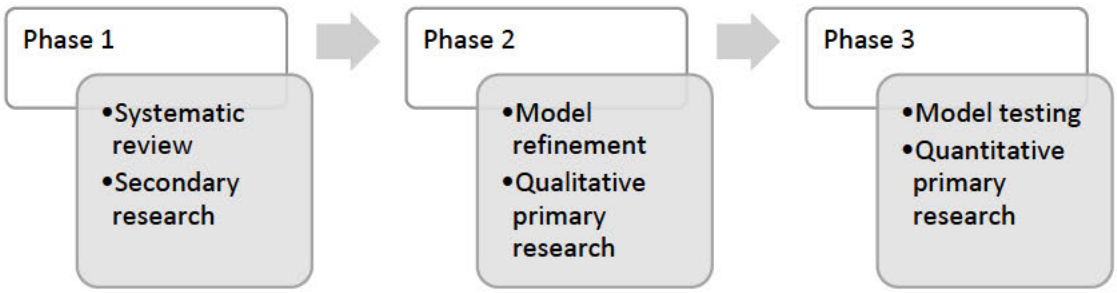

Figure 8 Three-phase research process

3.5. Research Philosophy

Overall, the research follows a pragmatic research paradigm, accepting that reality and knowledge are socially constructed and that no best approach is suitable for complex social issues (Kaushik & Walsh, 2019, p. 2). This approach aligns with the mixed methods research design, with the primary research in Phase 2 being qualitative and Phase 3 being quantitative. Phase 2 was for refinement and verification of the initial model by a panel of industry and academic experts in WAINs. This phase followed a qualitative, exploratory design grounded in the interpretive tradition to gain an in-depth understanding of WAINs. An interpretivistic research paradigm was suitable to delve into the WAIN experts' experiences and knowledge of their networks and women in AI careers. Interpretivists believe that understanding phenomena is best conducted on a more subjective basis, where human experience and perceptions are valued (du Plooy-Cilliers et al., 2021, p. 27). Additionally, interpretivism supports the ontological view that reality is socially constructed from the viewpoint of the people involved (du Plooy-Cilliers et al., 2021, p. 27), in this case, women in AI.

Phase 3 of the research sought empirical evidence of the relationship between networking behaviours and women in AI careers, following a positivistic tradition

(Sekaran & Bougie, 2016, p. 28). Networking behaviour is a social construct; thus, it is more accurate to position this research in the post-positivism tradition, which recognises that there are no absolutes in human behaviour (Creswell, 2003, p. 7). However, unlike the previous phase, which employed an interpretivist lens, this phase was epistemologically aligned with positivism, seeking empirical, objective evidence through numerical observations (Creswell, 2003, p. 7). Networking behaviour is viewed objectively and measured independently of human interpretation, in line with the ontological view of positivism that reality can be measured and predicted (du Plooy-Cilliers et al., 2021, p. 25). This phase of the research aimed to test the relationships between networking and AI careers with a view to the generalisation of results; thus, axiologically, the paradigm supports objectivity and value-free research methods (du Plooy-Cilliers et al., 2021, p. 25).

The first phase of the research employed a secondary research process, while the latter two were primary, as seen in Figure 3 above. Using the notation developed by Creswell (2012, p. 538), the design approach was: QUAL -> quan since only the last phase was quantitative. This design allowed for the exploration of the issues, with the results of one phase informing the data collection of the subsequent phase (Creswell, 2012, p. 544).

The remainder of this methodology chapter is organised per phase, including the specific objectives each phase sought to achieve.

3.6. Phase 1

The systematic review in Phase 1 had the objectives below:

- To broadly categorise social causes of gender bias in AI algorithms.
- To outline the social consequences of algorithmic gender bias on women and gender minorities.
- To explore proposed social solutions to AI gender bias.

The various elements related to the methodology followed in Phase 1 follow.

3.6.1. Research design and methods

Rather than a primary study that would only add more detail to a narrow area of the topic, a systematic review provides a precursor to further research (Petticrew & Roberts, 2008, p. 28), in this case on AI gender bias, so that the problem can move forward to finding potential solutions. A systematic review is an exacting methodology for finding, analysing and reporting literature in a specific, precisely defined area producing a replicable and transparent synthesis of the current state of knowledge (Denyer & Tranfield, 2009, p. 672). By following a rigorous scientific approach, relevant literature is organised, and evidenced-based decisions are made about knowledge gaps (Petticrew & Roberts, 2008, p. 9) in the field of gender bias in AI algorithms. The key principles of systematic reviews include a lack of bias by using a well-defined protocol to ensure validity, rigour and replicability (Shamseer et al., 2015, p. 1). This way, the results can be used confidently to inform practice, policy and future research direction (Denyer & Tranfield, 2009, p. 675). By explicitly targeting gender bias, a homogenous set of results resulted from the review, allowing for aggregation and synthesis of results.

3.6.2. Population and sampling

The Population, Intervention, Comparison, Outcomes and Context (PICOC) framework for systematic review research questions (Petticrew & Roberts, 2008, p. 42) provided a formal and specific method in Phase 1. Similar to the process used by Baleis et al. (2019, p. 5), the application of the PICOC framework for this study was: the Population being women, the Intervention/Indicator was gender bias in AI algorithms, with the Outcome being the effect of gender bias in a global context.

3.6.3. Data collection

The data collection procedure followed a strict protocol to ensure an explicit and transparent description and justification of the process followed. The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) protocol was selected since it is the preferred method for ensuring a rigorous review and is used by other systematic reviews on the topic of algorithms (e.g. Favaretto et al., 2019, p. 4; Wieringa, 2020, p. 1).

A scoping review using Google Scholar determined the size and scope of the review, as recommended by Tranfield, Denyer, and Smart (2003, p. 214), due to the cross-disciplinary nature of the topic. This exercise informed the search strategy for the review, including search terms, type of literature and study period (Linnenluecke, Marrone, & Singh, 2019, p. 181). The results also determined that this review was not duplicating an existing review on algorithmic gender bias. In their systematic review of fairness and big data, Favaretto et al. (2019, p. 23) cite the lack of grey literature as a limitation and recommend that future studies include it. For this reason, and based on the scoping review, grey literature in the form of conference proceedings and reports was included in this review.

Kitchenham and Brereton (2013, p. 2067) and Adams, Smart, and Huff (2017, p. 435) recommend the following databases for inclusion in business and software engineering systematic reviews: IEEE, ACM, SCOPUS, Web of Science, EBSCOHost and PsychInfo. Selection from this list for this review was guided by reviewing the databases used by systematic reviews in the general field of AI fairness and bias (Favaretto et al., 2019, p. 3; Khalil, Ahmed, Khattak, & Al-Qirim, 2020, p. 130752; Wieringa, 2020, p. 1) resulting in the final selection of IEEE Xplore, ACM Digital Library, SCOPUS, and Web of Science for this review. The search terms were sourced from the focus area of AI algorithms. The factor of interest was gender bias, similar to the process followed in the review by Khalil et al. (2020, p. 130752). Synonyms for keywords were derived from key studies on the issue (Wieringa, 2020, p. 14). Boolean operators were used to combine the keywords from which the following search string was generated:

("gender bias" OR sexist OR "gender discrimination" OR "gender diversity" OR "gender inequality") AND (Algorithm OR Algorithmic OR "machine learning").

3.6.4. Data preparation

For the systematic review in Phase 1, data was prepared based on inclusion and exclusion criteria. According to Shamseer et al. (2015, p. 9), the PRISMA protocol specifies two types of eligibility. The first stems from the characteristics of the study itself. In this case, eligible studies had to be focused on gender bias, the gender bias must have arisen from machine learning algorithms, and the study must have included causes or consequences of the bias or offer potential solutions. The second stems from the characteristics of the report, including time frame, language, and publication

types. Large-scale deployment of machine learning algorithms is a relatively recent development (OECD, 2019, p. 21) and the consequences of bias have only recently become a pressing issue (Kochi, 2018, p. 7). Therefore, this review focused on papers from the last ten years, similar to other systematic reviews on AI bias (Baleis et al., 2019, p. 10; Favaretto et al., 2019, p. 4). Languages other than English were excluded, supporting replicability (Wieringa, 2020, p. 15), practicality and the multi-disciplinary nature of the topic. There were no restrictions based on the discipline. Publication types were restricted to journals, conference proceedings and think tank reports. There were no exclusions based on methodology, allowing empirical, theoretical and conceptual papers to be included.

3.6.5. Data analysis

Data extraction was conducted using Distiller SR, software designed to facilitate systematic reviews (Shamseer et al., 2015, p. 10). The initial search produced 3401 unique papers, with 2752 excluded after an initial screening of the title and abstract. A further 471 papers were excluded upon further review of the whole paper, mainly for not including gender bias specifically. The resulting 177 papers covered both technical and social causes, consequences and solutions. Only social aspects were considered for this review; therefore, 112 technical-only papers were excluded, resulting in 57 papers. By following references, based on seminal papers and the Pearl or snowball method, an additional eight papers were added, resulting in a final total of 64 papers. The results of this process can be seen in Figure 9, the PRISMA flowchart.

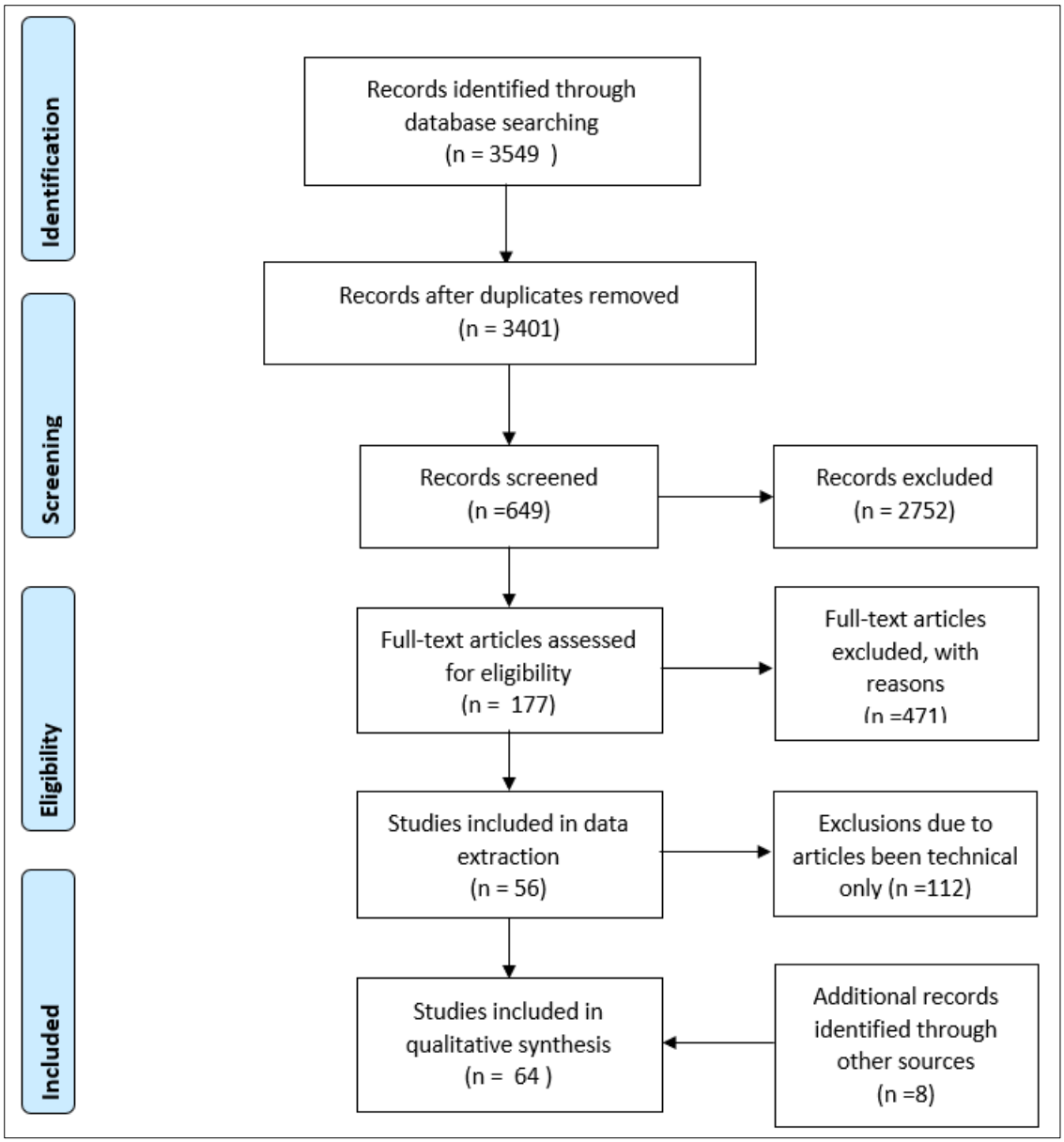

Figure 9 The PRISMA flowchart

Draude et al. (2019, p. 325) developed a multi-disciplinary, socio-technical framework used in this review. This framework presents a socio-technical gender perspective where bias is shaped by the society generating the data, which is fed into the algorithms. In contrast, technical bias arises from the models and features of the algorithm itself, and emergent bias stems from how the algorithm is used. The data analysis started by first separating out the papers with a social perspective. Thus data analysis followed a deductive approach based on the literature review and research questions, which yielded themes suitable for thematic analysis (Fereday & Muir-Cochrane, 2006, p. 83). The three themes that followed the code book structure presented by Fereday and Muir-Cochrane (2006, p. 85) were social causes,

consequences and solutions related to gender bias in AI algorithms. Direct-quote evidence of the themes was captured and categorised in the Distiller SR software and then imported into Nvivo for rich, in-depth analysis of the themes. The results of which can be found in Phase 1 findings in Chapter 4.

3.6.6. Data quality

In the systematic review, articles included for review were screened for quality of reporting and methodology (Kitchenham & Brereton, 2013, p. 2054). The DistillerSR AI toolkit screened the manual reviews and suggested 28 exclusion discrepancies, which were then manually checked. A second reviewer tested a portion of randomly selected articles from each review level as an additional reliability check. The number of studies included, the research method and evidence quality all contributed to data quality (Linnenluecke et al., 2019, p. 182).

3.7. Phase 2

The objectives for this phase were:

- To explore WAIN experts' opinions on the causes for a lack of women in the AI profession and the benefits of increasing gender diversity in AI.
- To explore how WAINs support women in persisting and advancing in AI careers.
- To explore the role of gender and professional identity in WAINs.
- To refine and verify the initial conceptual model from the perspective of WAIN experts.

3.7.1. Research design and methods

The research design for Phase 2 was qualitative and exploratory – exploring the experts' views on women in AI, AI careers, networking behaviours and the relationships between the constructs. Exploratory research served the purpose of confirming the initial conceptual model and gaining new insight before testing the model (Davis, 2014, p. 75). A qualitative methodology is helpful in "exploring a problem and developing a detailed understanding of a central phenomenon" (Creswell, 2012, p. 16) and was thus suitable for this phase. du Plooy-Cilliers et al. (2021, p. 31) argue that interpretivists rely on qualitative research as they seek a deep understanding of

social realities. Thus, a qualitative methodology is appropriate for this phase in exploring the experiences of women in AI. A flexible research design was also needed, as with most studies exploring an unknown area (Davis, 2014, p. 75).

3.7.2. Population and sampling

Pascoe (2014, p. 133) explains that target populations refer to the population members from whom data can be collected, while the accessible population is the subset of the target the researcher has access to. Phase 2's population comprised women in the AI profession who either represented the network on a country or region basis or fulfilled another organisational role, such as social media lead or content lead. Experts on WAINs were purposively selected to form an expert panel to review the conceptual model developed in Chapter 2, the Literature Review. The accessible population was the leadership of the WAI network. The leadership consists of ambassadors representing the Women in AI network in various countries and various lead positions such as partnerships, research and social media.

Purposive, non-probability sampling was selected, consistent with the qualitative methodology chosen for this stage. According to Rubio, Berg-Weger, Tebb, Lee, and Rauch (2003, p. 96), six to ten experts should make up an expert panel. Since the experts were relatively homogeneous in the specific type of knowledge required to develop the model, a sample size of seven was selected. Participants were purposively sampled based on gender, expertise, experience in global women in AI networks and working in the AI profession. The participants all identified as women, reflective of the overall leadership, however experts were of various backgrounds and nationalities and in different time zones.

3.7.3. Data collection

Expert opinion interviews allow for the professional and personal experience of the experts to be exposed, aimed at revealing the experts' knowledge and insights (Döringer, 2021, p. 273). The data in Phase 2 was collected through synchronous semi-structured interviews conducted and recorded using Zoom video conferencing software. Online interviews are relatively common as a rich and dependable data collection method (Rahm-Skågeby, 2011, p. 417).

The in-depth interviews took place virtually over a few months towards the end of the pandemic stage of COVID-19. The interviews began with an explanation of the research's purpose, followed by a series of pre-set questions, loosely following the interview guide in Appendix C. The semi-structured interview allowed for further probing of answers and follow-up questions. The interview culminated in a graphical representation of the model displayed on the electronic screen to interrogate the relevance and applicability of the model components and relationships. Each interview was recorded for later analysis.

3.7.4. Data preparation

The online expert interviews were recorded, with permission from the participants, and then transcribed into a written narrative format. The transcriptions were checked manually for accuracy and then imported into NVIVO for processing.

3.7.5. Data analysis

For Phase 2 data analysis, a thematic content analysis of data gathered from the expert panel was conducted. The coding scheme was based on themes developed from the initial theory-based model. The hierarchical schema was broadly grouped around networking behaviour, outcomes, career persistence, and advancement. Thematic content analysis is a flexible method comprised of three steps: Elicitation, reduction and visualisation (Rahm-Skågeby, 2011, p. 418). The interview recordings were transcribed, prepared for analysis and then analysed using NVivo (Creswell, 2012, p. 243).

The interview data was then analysed using thematic qualitative content analysis, following an open coding process to unveil the experts' implicit knowledge and opinions (Döringer, 2021, p. 273). Using pattern coding, interview transcriptions were analysed in Nvivo to discover themes and common patterns. Pattern coding allows themes to emerge by assembling common codes as a secondary round of coding (Saldaña, 2021, p. 152). After a rigorous iterative process, the main themes were exposed, based on the research questions, and informed by literature.

3.7.6. Data quality

Phase 2 was qualitative research, which required trustworthiness (Sinkovics, Penz, & Ghauri, 2008, p. 690). Credibility, confirmability and dependability were ensured through participants verifying results (Rahm-Skågeby, 2011, p. 423) and accurate descriptions that are not over-reduced (Rahm-Skågeby, 2011, p. 424). Four dimensions of trustworthiness were required in this qualitative phase. The first was credibility, increased by member checks with participants in the expert panel, and through engagement with the WAI network. Credibility refers to how valid participants find the study results (Rahm-Skågeby, 2011, p. 423), and is increased when the researcher has prolonged engagement with participants, as was the case in this research where three years were spent engaged in WAINs (du Plooy-Cilliers et al., 2021, p. 295). Transferability, as the second dimension of trustworthiness, refers to whether a study's findings can be transferred to another setting (du Plooy-Cilliers et al., 2021, p. 296). Transferability was enhanced by the research site being the WAI network, made up exclusively of members of the network being researched. Further, with the model verified and refined by leaders of the WAI network, the model should be transferable to other women in AI networks. The third dimension - dependability, refers to the reliability and repeatability of a study, mainly through the procedure followed (du Plooy-Cilliers et al., 2021, p. 296) and was enhanced in this study by providing accurate descriptions that are not over-reduced (Rahm-Skågeby, 2011, p. 424). The expert panel validated the model, which is important in ensuring the final dimension of trustworthiness – confirmability. Each construct originated in the literature, based on pre-existing, validated scales, and were then checked in Phase 2 of the research with the expert panel to support construct validity (Koonin, 2014, p. 256).

3.8. Phase 3

The objectives of this phase were to:

- To investigate WAIN members' career persistence and advancement in the AI profession.
- To investigate WAIN members' networking behaviour.
- To examine WAIN benefits and resources.
- To determine the relationships between networking behaviour and WAIN.

member career persistence and advancement in AI.

3.8.1. Research design and methods

This phase employed a quantitative research method in support of the post-positivistic research philosophy requiring objective, empirical data collection and analysis (du Plooy-Cilliers et al., 2021, p. 33). Methodologically, quantitative research aims to find valid and reliable relationships through statistical analysis (du Plooy-Cilliers et al., 2021, p. 34), which this phase of the research tested. Numerical data on networking and women in AI careers was collected via a cross-sectional survey and analysed statistically to test the model from Phase 2. The research design was quantitative and predictive – to test the relationship between networking behaviours and AI careers. Networking behaviour and the resources and opportunities provided by the network were tested to establish if these supported Women in AI careers. The primary aim was to determine whether there are relationships between the main variables in the study (Davis, 2014, p. 76). The hypotheses assumed that increased networking behaviour would enhance women's advancement and persistence in AI. Descriptive research, which aims to improve information about a phenomenon (du Plooy-Cilliers et al., 2021, p. 86) was used to describe networking behaviours, resources and opportunities.

3.8.2. Population and sampling

Phase 3's target population was all formal Women in AI network members. The accessible population was members of the Women in AI network, an international WAIN with a presence in over 115 countries (WAI, 2021, para 4). A sampling frame is a list that contains all members of the accessible population (Pascoe, 2014, p. 136), which for this phase was the membership list of the WAI network. This network uses Slack as its communication platform, an online messaging application primarily used for business or professional purposes. The WAI Slack community matched the population parameters: female, network members, and in AI careers. By Phase 3 of the research, the Slack membership list had grown to 5869. Probability sampling ensures each member of the WAI network has an equal chance of being selected to represent the accessible population (du Plooy-Cilliers et al., 2021, p. 152) and supports the objective of generalisable results (Sekaran & Bougie, 2016, p. 22). A sample size of 361 members was required, with a margin of error of 5% to allow inferences to the broader population.

Systematic probability sampling was selected as the sampling method, suitable for quantitative data collection, where the sample was randomly chosen from the membership list using a sample interval (du Plooy-Cilliers et al., 2021, p. 155). The sample interval was 16, based on the population of 5869. After obtaining permission from a WAI network leader (see gatekeepers' letter in Appendix B), a link to the survey was sent via Slack to the sample, together with the informed consent letter (see Appendix A). After two weeks, only 85 responses were received. To improve the response rate, each network member was then sent a link with a request to complete the survey, which is, in effect, a census, also suitable for quantitative research (Parker & Gallivan, 2011, p. 2). This sampling method is also known as a full coverage probability sample where all members had an opportunity to be represented in the survey while ensuring unbiased results and increasing generalisability (Parker & Gallivan, 2011, p. 4). A census is practical as it was unknown how active the members were in Slack, and a census mitigates self-selection bias typical in online sampling (Fricker, 2008, p. 196). An acceptable 212 responses were received over a two-month period.

3.8.3. Data collection

In Phase 3, the conceptual model refined in Phase 2 was tested through a self-administered and electronically distributed questionnaire (see Appendix C). The WAI members were sent a structured questionnaire where the constructs in the model were measured. The international nature of the WAIN, with representation in over one hundred countries, meant that an electronically distributed survey was the most practical data collection method. The standardised questionnaire used in this phase allowed for structured responses to composite questions using scales explained below.

Variables and Scales

The main variables in the study originated in the literature and were verified and expanded upon in Phase 2 of the research - the expert review. Each variable was measured using a previously validated scale with minor variations. The scales consisted of a set of related Likert-based questions, with high internal consistency measured by Cronbach's alpha as recommended by Tavakol and Dennick (2011, p. 53). The independent variable was networking behaviour, and the dependent variables

were AI career persistence and AI career advancement. The mediating variables were network opportunities and resources and network support.

Networking behaviour: Early research resulted in a multi-dimensional scale consisting of five primary networking behaviour constructs (Forret, 2014, p. 6) of which maintaining contacts and professional activities are relevant to this study. Wolff's multi-faceted scale developed from an inductive, theory-based study, built on confirmatory factor analysis, and was validated in subsequent studies (e.g. Wolff, Schneider-Rahm, & Forret, 2011, p. 245; Wolff & Spurk, 2020, p. 278). Porter and Woo (2015, p. 4) systematically reviewed research into networking behaviour. They found that Wolff's network construct and resultant scale were particularly useful in providing an insightful and comprehensive measure of network behaviour and rated it the highest quality networking scale (Porter & Woo, 2015, p. 4). Further, other scales include concepts not directly or specifically related to networking or have not been validated (Wolff & Spurk, 2020, p. 280). Thus the short networking behaviour scale was selected for this research, with multiple tests indicating reliability with Coronach's Alphas averaging over .7 (Wolff & Spurk, 2020, p. 289).

Career persistence: refers to WAIN members staying in the AI profession and not planning to leave their current AI job. A positive association is indicated through commitment to the AI profession, similar to commitment to the IT profession (Brooks et al., 2015, p. 23). Career persistence was measured using the scale by Brooks et al. (2015, p. 23) designed to measure intention to stay through affective commitment to a profession, in this case to the AI profession. The scale is comprised of five Likert items and has a Cronbach's' Alpha of .87 (Brooks et al., 2015, p. 14). The same variable was also used by Armstrong et al. (2018, p. 33) for career persistence when expanding Ahuja's model, which was used in the original conceptual model developed in Chapter 2.

Career advancement: considers how satisfied women in AI are with their progress in their careers, and was measured using the five item career satisfaction scale by Spurk, Abele, and Volmer (2011, p. 326), who conducted a series of tests on the scale with an average Cronbach's alpha of over .8. The scale has been used in multiple studies about careers (e.g. Kundi, Hollet-Haudebert, & Peterson, 2021; Salleh, Omar,

Aburumman, Mat, & Almhairat, 2020, p. 5) and by Abubakar (2020, p. 74) in relation to AI.

Network support was measured using the social provisions scale, devised by Steigen and Bergh (2019, p. 1695) with high reliability as measured by Cronbach's Alpha of .88. Despite being a relatively recent scale, it has been well-cited and validated (e.g. Orpana, Lang, & Yurkowski, 2019, p. 324).

Opportunities: The network opportunities variable was measured using the resources and learning scale developed by Hirschi et al. (2018, p. 342), applied to measure learning and career opportunities that WAINs offer. The scale Cronbach's Alpha of .80 shows the reliability of the scale, which has also been used in other studies, as described in an article on career success by Haenggli and Hirschi (2020).

Research instrument

The research instrument used to collect data for this phase was a close-ended questionnaire, as surveys are useful for collecting descriptive behavioural data (Sekaran & Bougie, 2016, p. 97). The survey was administered once-off, employing a cross-sectional design (Sekaran & Bougie, 2016, p. 104). The questionnaire was constructed using Google Forms, a low-cost and efficient online survey method that is easy and convenient for respondents (Sekaran & Bougie, 2016, p. 242). However, online surveys have a notoriously low response rate (du Plooy-Cilliers et al., 2021, p. 147; Sekaran & Bougie, 2016, p. 143) which was no different in this research. Other disadvantages, such as literacy and computer literacy (du Plooy-Cilliers et al., 2021, p. 170) were not a problem because the respondents were in the AI profession.

The survey link, an explanation of the purpose of the research and the informed consent letter (see Appendix A) were sent to WAI members. The questionnaire was designed for simplicity and ease of completion, with good overall flow and aesthetics (Sekaran & Bougie, 2016, p. 145). Respondents were required to confirm their consent by clicking on the link to proceed to the first section of the questionnaire. As can be seen in Appendix B, the body of the questionnaire began with a series of questions about the respondent's career in AI. These introductory questions were followed by a section on the respondent's networking behaviour. The following two sections consisted of questions about the support and opportunities offered by the network. The

questionnaire concluded with demographic questions about the respondents, as recommended by du Plooy-Cilliers et al. (2021, p. 157). All questions were purposefully selected in line with the research objectives and presented in a logical and objective order (Sekaran & Bougie, 2016, p. 150).

The main variables were measured with 5-point Likert scales, suitable for measuring opinions and levels of agreement (Leung, 2011, p. 412). The Likert items had a statement regarding the construct being measured, followed by the measurement of the level of agreement with the statement (du Plooy-Cilliers et al., 2021, p. 159), where a five represented strongly agree, a one strongly disagree, and a three offered a middle neutral option (Willits, Theodori, & Luloff, 2016, p. 134). Other scales used were nominal, allowing categorisation of answers (Sekaran & Bougie, 2016, p. 208) and scalar for numbers in a validated range of continuous data for items such as age and years of membership.

The questionnaire was pretested to check for errors and ambiguity in the wording and flow. The time estimate of ten minutes to complete was also tested. Participants from Phase 2 of the research and a further three pre-testers, selected using convenience sampling, were requested to try the questionnaire over one week before the survey went live. Apart from some changes to the wording of the request to complete the survey and the suggestion to add an incentive, no other feedback was received that resulted in changes to the questionnaire. The final version of the questionnaire was sent to the WAI membership list via a personal message over three weeks. After two months, with 212 responses, the data was downloaded for analysis.

3.8.4. Data preparation

The 212 cases from the survey in Google Forms were downloaded into Microsoft Excel for initial screening. First, the cases were screened for missing data. Six cases were removed where missing values accounted for over 20% of the case. For eight cases where missing data was less than 5%, the missing data was completed by computing the median and means as applied by Lorenzo-Seva and Van Ginkel (2016, p. 606). The data were also checked for unengaged responses, indicated by little to no standard deviations in answers to the scales, but none were found. The last check was for normality and kurtosis, where one kurtosis issue was found in the responses to the number of years in AI, meaning the distribution had a heavier tail (Kline, 2016, p. 74).

However, this was accepted as it is logical that the number of years would be skewed to the low side since the profession is in its infancy. After data cleaning, 206 cases remained, which meets the minimum required for exploratory factor analysis (EFA) (Howard, 2016, p. 52), an important step in the data analysis.

3.8.5. Data analysis

From Excel, the cleaned data was imported into IBM SPSS v28 for statistical analysis, in line with quantitative methodology. First, a sample profile was developed using descriptive statistics. Data were summarised in univariate analysis of the categorical questions. Further descriptive statistical analysis yielded frequency data which was then depicted graphically in bar and pie charts. The mode was used as a measure of centrality for discrete nominal data, being the most common response (Kahn, 2014, p. 212). For continuous data, the mean and standard deviation were calculated, and the results depicted in a histogram, as recommended by du Plooy-Cilliers et al. (2021, p. 214).

The variables measured by the Likert scales presented previously, such as networking behaviour, were also analysed using descriptive statistics. The Likert items for each scale were summated, and the composite scores analysed as a single interval scale. Although there are debates about treating summated Likert items as scalar, this is accepted practice when items measure the same construct (Wadgave & Khairnar, 2016, p. 67; Willits et al., 2016, p. 133). The Likert scales were tested for acceptable reliability using Cronbach Alpha, further supporting this practice (Leung, 2011, p. 413) and the appropriateness of parametric analysis of scales (Wadgave & Khairnar, 2016, p. 67). The mean and standard deviation were calculated to determine the averages and variations in results for each variable (Sekaran & Bougie, 2016, p. 284). Crosstabulations of demographic and other categorical data determined if there were any interesting associations.

The main objective of this research phase was to determine the relationship between networking behaviours, opportunities and resources, network support, and women in AI career persistence and advancement. To analyse the results for this purpose, structured equation modelling (SEM) was undertaken, which is suitable as SEM has

the objective of testing a theoretically-sound model's constructs, measured with observed variables (Kline, 2016, p. 10) and is considered best practice for researchers in the social sciences (Hooper & Coughlan, 2008, p. 53). First, in SPSS, a Kaiser-Meyer-Olkin test was used to determine sampling adequacy, and Bartlett's test of sphericity ensured that the correlations were statistically different (Howard, 2016, p. 52). The data was then analysed in three steps. A preliminary analysis of the model scales was undertaken through Exploratory Factor Analysis (EFA) using the software Statistical Package for the Social Sciences (SPSS) v.28, since the scales were adapted for applicability to WAINs. As suggested by Treiblmaier and Filzmoser (2010, p. 112), an EFA was conducted to confirm the validity of the scales in the model and for data reduction, as there were many indicators used initially, and some items in the model were derived from expert opinion. The EFA was undertaken in SPSS to test and validate a factor structure for the model's latent variables and reduce cross-loadings. The pattern matrix in the EFA was compared to the theoretical model, using recommended factor loadings (Howard, 2016, p. 60). The output of the EFA was checked through a Confirmatory Factor Analysis (CFA) in Analysis of Moment Structures (AMOS) v.24 as an additional control layer. The CFA path model was generated, depicted hypothesised relationships. Finally, hypotheses were tested through SEM, also in AMOS, a recommended sophisticated computer tool for SEM (Kline, 2016, p. 102). Bootstrapping multiplied the regression coefficients of the various paths analysis (Kline, 2016, p. 68) to determine the relationships, from which the null hypotheses could be accepted or rejected.

3.8.6. Data quality

Reliability and validity must be tested in quantitative research, including measuring the variables accurately (Sekaran & Bougie, 2016, p. 220). Reliability requires consistency and accuracy of measure used (du Plooy-Cilliers et al., 2021, p. 289) and was established by measuring the Cronbach Alphas of the variables (Cheung, Cooper-Thomas, Lau, & Wang, 2023, p. 3). Reliability was also enhanced by the methodology, which can be replicated (Koonin, 2014, p. 254) in that similar results would be expected were the research to be repeated. Composite reliability was also tested to check that the indices were above the threshold of 0.70 (Presbitero & Teng-Calleja, 2022, p. 8).

Construct validity requires that the measured items reflected the theoretical latent construct they were designed to measure (du Plooy-Cilliers et al., 2021, p. 293).

Elements of the model were, where possible, constructed from previously tested constructs and scales, enhancing construct validity, which supports internal validity (Bhattacherjee, 2012, p. 37). Further, the refined model and instrument development were checked and verified by the panel of experts, ensuring representational validity, which includes face and content validity (Bolarinwa, 2015, p. 196). A relatively short questionnaire was also used to reduce common-method variance as Podsakoff, MacKenzie, and Podsakoff (2012) recommend.

Probability sampling design assisted in generalisability, ensuring external validity (Bhattacherjee, 2012, p. 37). Kurtosis and critical ratios were used to check for normality and outliers (Kline, 2016, p. 74). Further, convergent validity verified that all items in the model were statistically significant using Average Variance Extracted while discriminant validity checked for redundancy (Cheung et al., 2023, p. 7). Common method bias was tested using the Harman single factor test, a suitable test in business research (Fuller, Simmering, Atinc, Atinc, & Babin, 2016, p. 3198). Results of data quality tests can be found in the Findings chapter.

3.9. Ethical Considerations

This study complied with all UKZN Research Ethics requirements. Given the phased approach to the research, three rounds of ethical clearance were obtained. The original ethical clearance letter and the subsequent amendments for each phase can be found in Appendix E. Research commenced only after receiving approval from the UKZN Research Office. For Phases 2 and 3 of the research, all participants were assured of their confidentiality, that their participation was voluntary, and that they could withdraw from the study at any time in line with guidance from the research office. Gatekeeper's permission was obtained from the research lead of the WAI network (Appendix A). The researcher and supervisor's contact details were provided to all participants. Security and privacy of interview and survey data was ensured through password protection. Interview and survey questions were carefully constructed to ensure no sensitive or embarrassing topics were introduced, consistent with ensuring that no harm came to the participants.

3.10. Conclusion

In summary, the research methodology followed a phased approach. Phase 1 followed the PRISMA methodology for systematic review; Phase 2 was a qualitative study, sampling WAIN experts to refine the conceptual model developed in Chapter 2. The final Phase quantitively tested the refined model results from Phase 2. The research design was thus mixed methods sequential, where the sampling, data collection and analysis all followed on from and aligned with the research design. The phased approach described in this chapter supports the overall research objective of exploring how WAINs support women in advancing and persisting in the AI field through a qualitative and quantitative lens. The findings resulting from each of these three phases, including a discussion of the results, can be found in the following chapter.

Chapter 4. FINDINGS

4.1. Introduction

This chapter presents the key findings from each phase of the research, as they relate to the research objectives. The results from the systematic review in Phase 1 provided a comprehensive and multi-disciplinary 'stock-take' of the literature on algorithmic gender bias particularly in terms of the social causes, consequences and suggested solutions. This helped to better understand this relatively new and under-researched phenomenon. Next, the qualitative expert opinion results are presented from Phase 2. Finally, the Phase 3 survey results are presented, with results of the SEM analysis into networking behaviour and career persistence and advancement.

4.2. Phase 1 Findings

The systematic review in Phase 1 had the objective of broadly categorising social causes of gender bias in AI algorithms, outlining the social consequences on women and gender minorities and exploring social solutions to AI gender bias. The rigorous systematic review of the current state of research into the social causes, consequences and solutions to AI gender bias produced several interesting results. The review was conducted using a socio-technical framework, with the focus on social causes, consequences and solutions. The initial screening included social and technical papers, in line with the socio-technical framework used for this phase (outlined in Chapter 3). There were 112 papers excluded for being technical only, with 21 of the final 64 including articles falling under both social and technical categories. Figure 10 shows the breakdown of papers along the socio-technical dichotomy:

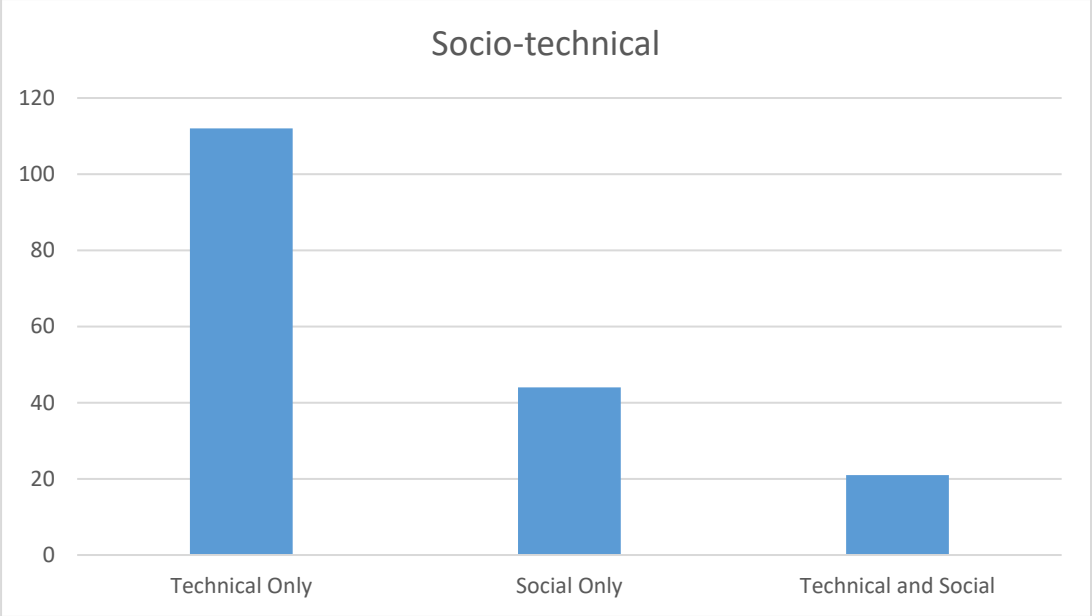

Figure 10 Social and technical focus of included papers

Of the included 64 papers, 31 were coded as including causes, 33 as covering consequences and 43 as covering solutions. Twenty-nine of the articles also referenced racial bias, among other types of biases. Despite searching for articles from 2010, Figure 11 shows that all of the included studies ranged from 2015 onwards, with 30 from 2020 alone and 75% from 2019 and 2020, signifying the recency of the topic. This finding also explains why over 50% of the articles were conference papers.

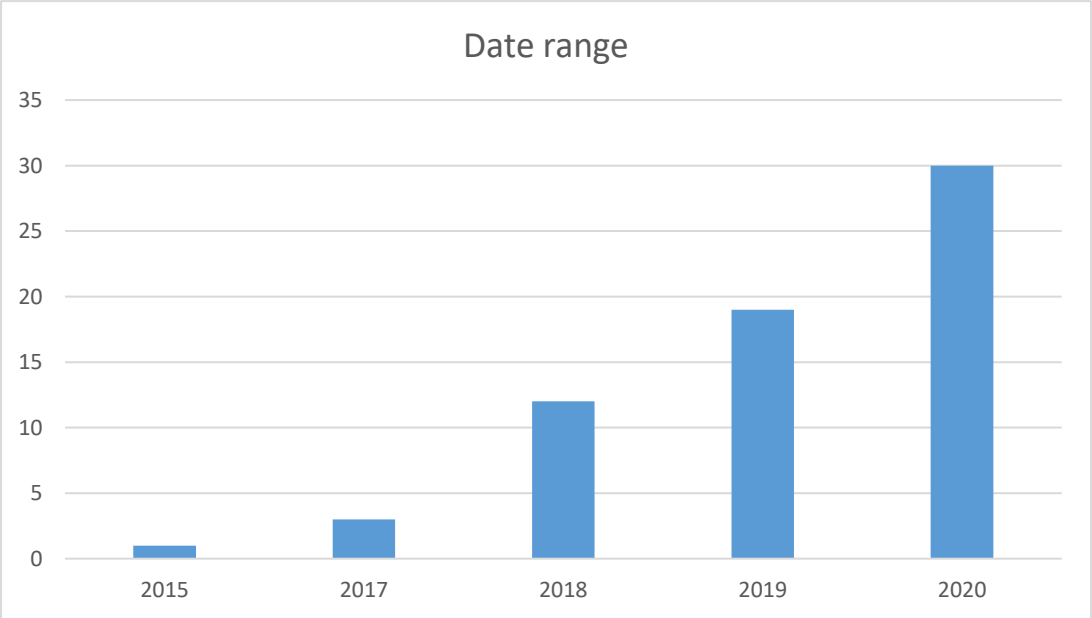

Figure 11: Date range of systematic review articles

The articles varied in domains, with 72% stemming from computer science, 25% from the social sciences and 3% from the health sciences. Specific subject areas reflect these general fields, with around 50% in AI ethics and AI. The remaining subject areas are shown in Figure 12 below:

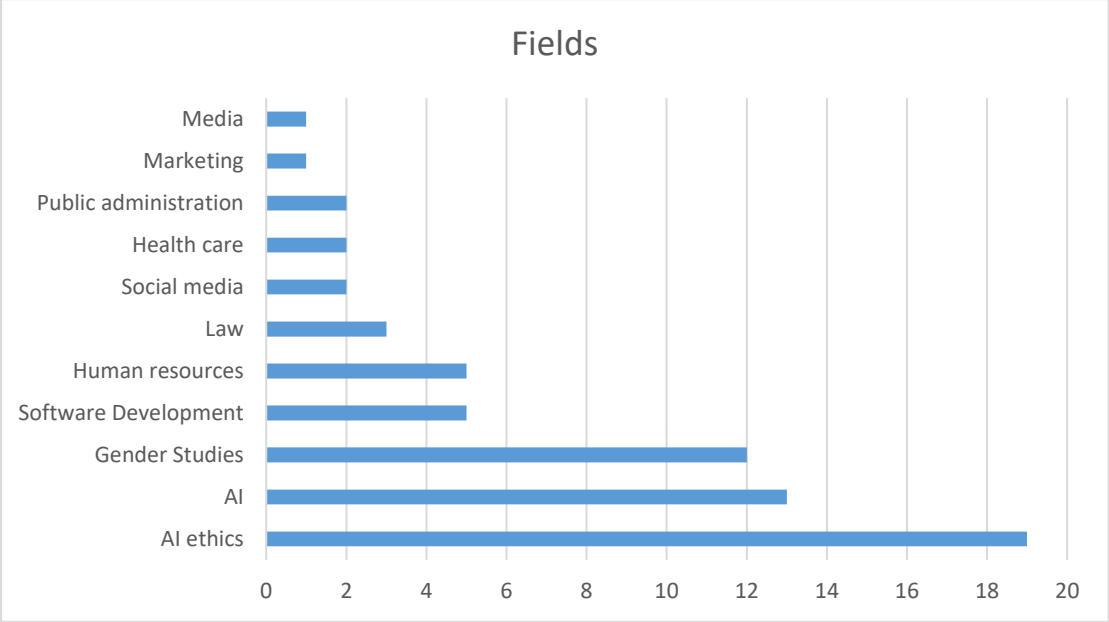

Figure 12: Fields represented by systematic review articles.

4.2.1. Social causes of algorithmic gender bias

For the social causes of gender bias, the articles were equally attributed to the design of AI algorithms and to the datasets they are trained on. Figure 13 shows that within the algorithmic design category, 43% were related to the lack of diversity in development teams, while 36% specified lack of awareness of bias in the algorithmic design process.

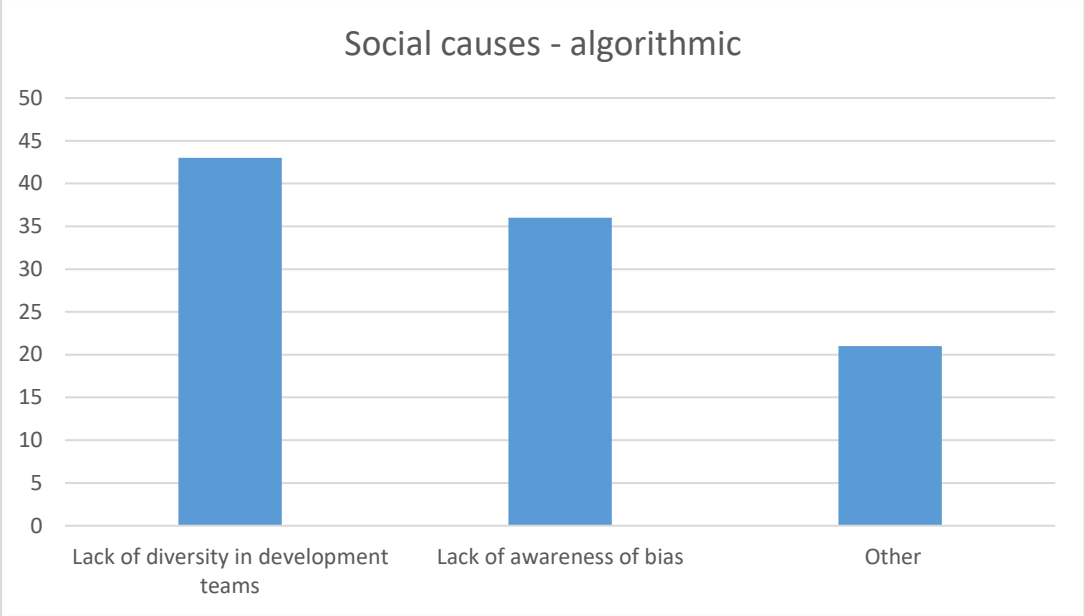

Figure 13 Sub-themes for the theme "algorithmic design" for social causes

One paper featured in the results was by Avellan, Sharma, and Turunen (2020, p. 142), who stated "homogeneous teams will share the same blind spots or cognitive biases that will transfer to their design of the technology, creating unbalanced and unfair outcomes." Bias is introduced at many points, including the design process (Singh, Chayko, Inamdar, & Floegel, 2020, p. 1285), with the many roles in AI development teams demonstrating a lack of diversity (Dillon & Collett, 2019, p. 19). Ntoutsi et al. (2020, p. 10) suggest that "representation-related biases creep into development processes because the development teams are not aware of the importance of distinguishing between certain categories" and that lack of diversity in development teams is one of the causes of AI gender bias.

For the dataset cause of gender bias, most articles (85%) referenced the lack of diversity in datasets. This finding is illustrated by Leavy et al. (2020, p.12) who state that "The source of this kind of bias often lies in the way societal inequalities and latent discriminatory attitudes are captured in the data from which algorithms learn". Wellner (2020, p129) agrees that gender bias arises from the training data, while Saka (2020, p. 1) explains that algorithms trained on big data containing gender stereotypes and underrepresented gender minorities will perpetuate those biases in the future. The 'Other' theme included gender bias arising from incorrect data classification, often at the intersection of race and gender. For example, a well cited paper by Buolamwini and Gebru (2018, p. 89) concludes with "the findings from this work concerning

benchmark representation and intersectional auditing provide empirical support for increased demographic and phenotypic transparency and accountability in artificial intelligence". Although this review only considered gender bias, it is important to note that AI bias can be even more pronounced for women of colour (Buolamwini & Gebru, 2018, p. 77).

4.2.2. Social consequences of algorithmic gender bias

Social consequences of gender bias in AI algorithms were wide-ranging in the articles, as depicted in Figure 14:

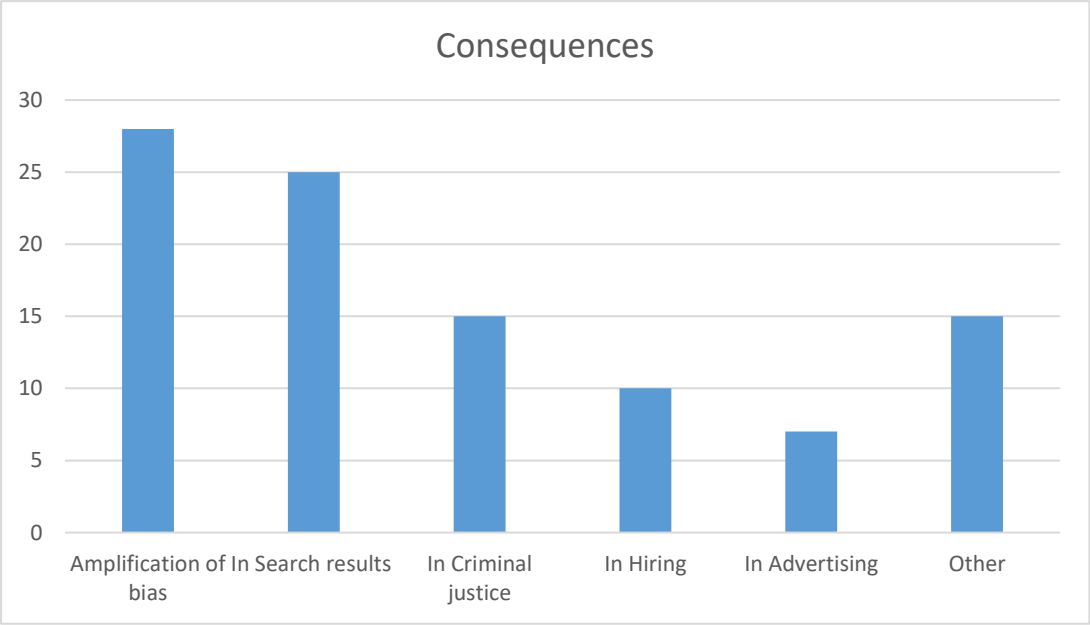

Figure 14 Social Consequences

The most commonly cited consequence was the amplification of gender bias, often creating a feedback loop: "Due to the feedback loop mechanism, the gender-biased results are fed back to the system, thereby deepening the biases" (Wellner, 2020, p. 129). The next most commonly coded consequence, at 25%, was that search results were biased, which included text, translation and image search results, most commonly from Google search. Leavy et al. (2020, p. 12) suggest that evidence of gender bias in recommender and search systems will profoundly impact society, given the pervasiveness of these tools in everyday use. Otterbacher, Bates, and Clough (2017, p. 6620) found a similar issue with Bing and how its image search algorithm tends to produce results that reinforce gender bias. Search text and translation results

often illustrated gender bias in profession or occupation. For example: “We then show that Google Translate exhibits a strong tendency towards male defaults, in particular for fields typically associated to unbalanced gender distribution or stereotypes such as STEM (Science, Technology, Engineering and Mathematics) jobs” (Prates, Avelar, & Lamb, 2020, p. 6364).

Gender bias had consequences in many fields; those that came up most frequently were criminal justice (15%), hiring (10%) and advertising (7%). Criminal justice manifests intersectionally, with black women the most adversely affected (Fernández-Martínez & Fernández, 2020, p. 213; Hamilton, 2019, p. 147). In hiring, Leicht-Deobald et al. (2019, p. 381) explain that recruitment algorithms may be “actively reifying the original gender bias” while Google’s advertising algorithm tends to bypass non-binary gender choices when personalising adverts (Shekhawat, Chauhan, & Muthiah, 2019, p. 281). In the ‘Other’ category, bias was found in facial recognition, education, automated personal assistants and surveillance (Whittaker et al., 2018, pp. 12, 15).

4.2.3. Social solutions to algorithmic gender bias

The final category considered papers proposing social solutions, with Figure 15 showing the emergent themes: 57% of the articles were coded as improving algorithmic design and 33% as improving due process. The remainder fell under the improving diversity in datasets category, with the solution emerging as ensuring the data is representative (Avellan et al., 2020, p. 143) and that gender bias is removed in cleaning up datasets (Parsheera, 2018, p. 7).

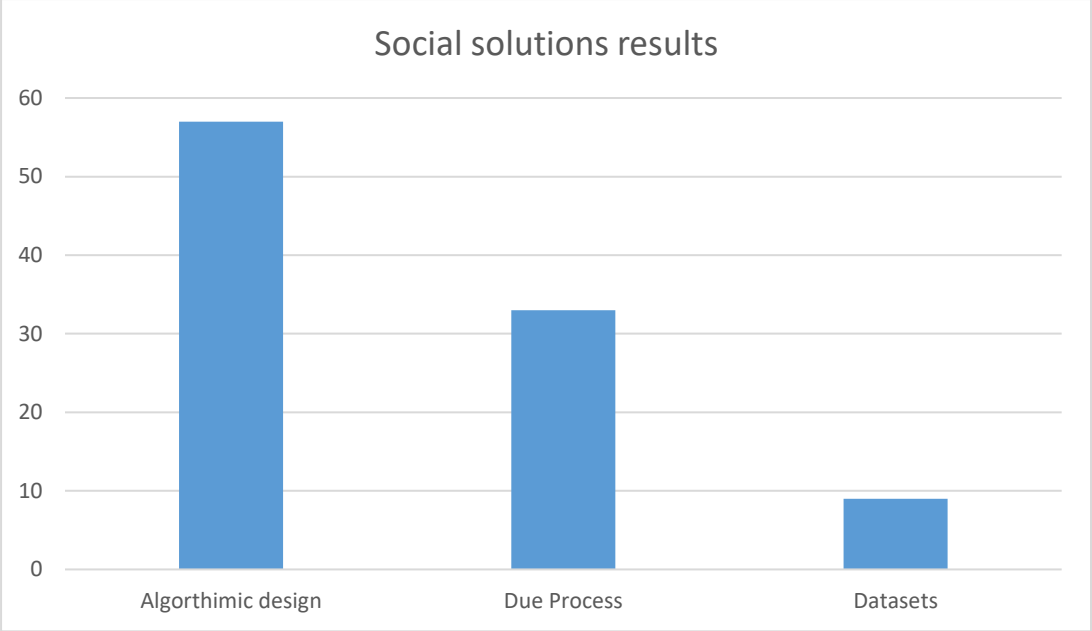

Figure 15 Overall results for Social Solutions

Within the algorithmic design theme, four main sub-themes emerged. These are depicted in Figure 16 below:

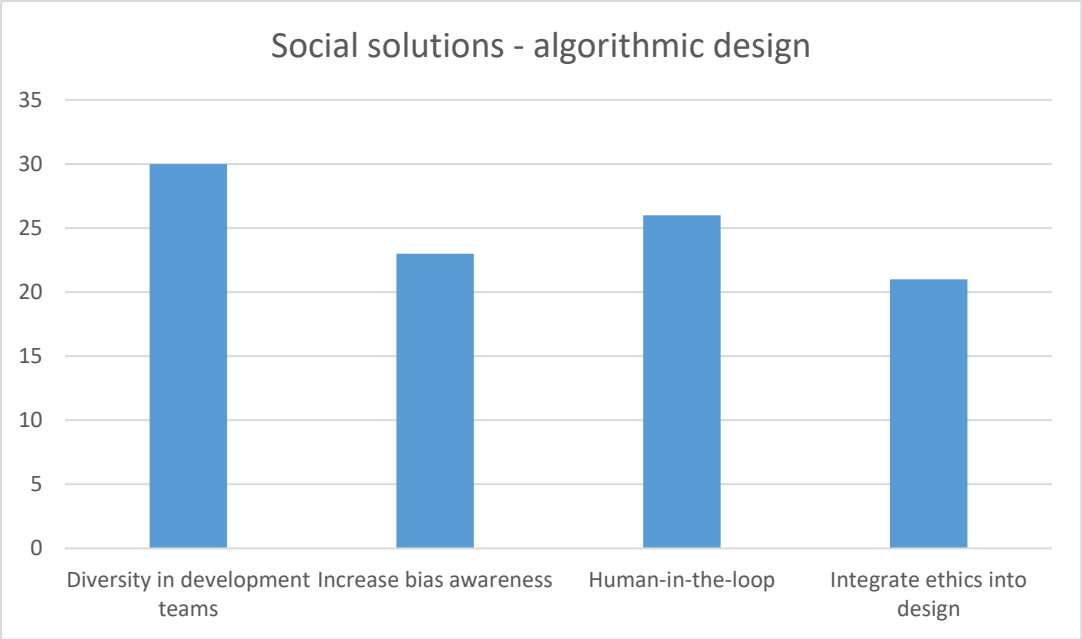

Figure 16 Social solutions related to Algorithmic design

Improving diversity in development teams was the most common solution proposed (30%). For example: “increasing gender inclusion in the development of AI technologies will introduce important and diverse perspectives, reduce the influence of

cognitive biases in the design, training, and oversight of learning algorithms, and, thereby, mitigate bias-related risk management concern" (Johnson, 2019, p. 1214). Saka (2020, p. 1) contends that recent studies on gendered algorithmic bias show that increasing the number of diverse designers and developers of algorithms can mitigate discriminatory outcomes.

Increasing awareness of bias within the algorithmic design and development process (23%) is demonstrated by Wellner and Rothman (2020, p. 191), who state that "Users and developers should be aware of the possibility of gender and racial biases, and try to avoid them, bypass them, or exterminate them altogether".

Human-in-the-loop, a term gaining prominence in socio-technical solutions, refers to the importance of humans in automated systems, especially in regulating AI (Rahwan, 2018, p. 6). The Human-in-the-loop solution coded at 23%, illustrated by Gilbert and Mintz (2019, p. 66), who urge "engineers to interpret themselves as part of this context, which includes the wider machine learning community as well as potentially-vulnerable populations of protected social categories".

A final solution that emerged under the algorithm design theme was to integrate ethics into the algorithm design process, at 21%, by creating and implementing a gender-inclusive code of AI ethics (Badaloni & Lisi, 2020, p. 13). Due process made up 33% of the social solutions to gender bias, with the emergent codes shown in Figure 17.

Figure 17 Social solutions related to Due Process

In the Due process theme, 36% of proposed solutions were aimed at improving fairness, accountability and transparency. Fairness is illustrated by Weyerer and Langer (2019, p. 511) where they state that "the development of strict and fair decision rules of AI applications that limit any conclusion based on non-relevant personal characteristics such as race, gender, etc. is vital to prevent AI-based discrimination". Regarding accountability, the article by Raji et al. (2020, p. 33) is an example of a study where they "contribute to closing the accountability gap in the development and deployment of large-scale artificial intelligence systems". Transparency is a key recommendation by West et al. (2019, p. 4): "Remedying bias in AI systems is almost impossible when these systems are opaque. Transparency is essential and begins with tracking and publicizing where AI systems are used, and for what purpose". Auditing was proposed as a due process solution to algorithmic bias (20%). Raji et al. (2020, p. 33) created a "framework for algorithmic auditing that supports artificial intelligence system development end-to-end, to be applied throughout the internal organization development lifecycle". Legal regulations to address algorithmic bias made up 28%, for example, Busuioc (2020, p. 10) suggested "Regulatory efforts are thus vitally needed to ensure that AI tools are brought to bear in a thoughtful and effective manner".

Within the social context, the results demonstrate that gender bias can be introduced at multiple points, from algorithm design, datasets and use of AI (Singh et al., 2020, p.

1285), similar to the Causes theme results. Causes related to training data bias and lack of gender diversity in programming teams are corroborated empirically in a study by Cowgill et al. (2020, p. 3).

Although all consequences of AI gender bias emerging from this review are serious, the most cited consequence is amplification via the feedback loop. “Algorithmic bias has the capacity to amplify and perpetuate societal bias, and presents profound ethical implications for society” (Leavy et al., 2020, p. 12). The consequences are far-reaching, multidisciplinary, and touch multiple industries and fields, creating further “discrimination and invisibilisation of women” (Gutierrez, 2021, p. 447).

4.2.4. Discussion of Phase 1 Results

A nuanced approach is needed when considering the issue of algorithmic gender bias, as the results of this review show that bias exists intersectionally, particularly for black females (Buolamwini & Gebru, 2018, p. 89). Further, gender is not a binary issue, and further research and solutions are needed to ensure genuinely inclusive algorithmic decision-making, accounting for all sub-groups (UNESCO, 2020). The issue of AI bias should be considered from a social, interdisciplinary perspective (Cheng, Varshney, & Liu, 2021, p. 27). Similarly, Whittaker et al. (2018, p. 36) recommend: “Expand the disciplinary makeup of those engaged in AI design, development, and critique, beyond purely technical expertise”. Treating algorithmic bias as a technical issue and focusing on debiasing training data is too simplistic and can still create discriminatory outcomes (Marda, 2021, p. 15). Further, a techno-centric view fails to consider the vital role of humans in the various stages of the AI lifecycle and the consequences for society (Marda, 2021, p. 18).

The first research objective for this phase was *“To broadly categorise social causes of gender bias in AI algorithms*”. Lack of awareness of how AI can result in biased output emerged as a social cause of AI gender bias, which was not an expected finding as it is not commonly cited. However, Leicht-Deobald et al. (2019, p. 377) suggest that ethical awareness of reducing gender bias is an important element in overcoming AI bias challenges, which has precipitated a move to more ethical AI (Schwartz et al., 2022, p. 39). From a social perspective, an important finding was the lack of diversity in development teams. Gender imbalance in development teams can result in biased

solutions with technical consequences (Avellan et al., 2020, p. 142). This finding forms part of broader initiatives to include more humans-in-the-loop, which considers social causes and the importance of societal impacts (Rahwan, 2018, p. 9). These results demonstrate the need to find ways to keep women in AI careers to ensure diversity of development teams and humans-in-the loop.

The second objective was "*To outline the social consequences of algorithmic gender bias on women and gender minorities*". The consequences of gender bias were shown to be far-reaching across multiple industries and areas of concern. As research proliferates into AI ethics and the consequences of AI, more social areas will be included, for example, with the proliferation of large language models such as ChatGPT (Nemani et al., 2023). Amplification of bias emerged as a common consequence and is also one of the most disturbing. Zou and Schiebinger (2018, p. 325) state that bias in algorithms reflects deep yet often subtle biases in society, which are then amplified in feedback loops due to the flawed algorithms, a finding supported in a recent survey by Nemani et al. (2023, p. 6). These findings indicate the imperative to find solutions to the problem, such as networks to support women in AI, as this research is concerned with.

The final objective of this phase was *"To explore proposed social solutions to AI gender bias."* The solutions begin with acknowledging and recognising that improving awareness of the problem is a good start. Having human oversight extends to the Due Process category. Many studies have been dedicated to fairness, accountability, transparency and auditing of AI algorithms to mitigate bias (e.g. Jobin, Ienca, & Vayena, 2019, p. 395; UNESCO, 2020, p. 25). After reviewing 24 studies, Khalil et al. (2020, p. 130759) determined that further research was needed into auditing algorithms and benchmarking databases. Good governance, public and private sector policy and regulatory frameworks are being actively pursued in research and practice (Dillon & Collett, 2019, p. 4; West et al., 2019, p. 39) as part of the growing field of AI ethics. Social solutions link back to social causes; for example, diversity in AI development teams emerged as a leading cause and solution. This is corroborated by several recent studies, with Dillon and Collett (2019, p. 5) contending that "Diversification of the AI workforce will be vital in order to design and implement technology which is equitable". UNESCO (2020, p. 14) recommends inclusiveness and parity for women in AI development teams. As expected, another social solution

around algorithmic design emerged as ensuring human oversight, classified as humans-in-the-loop. For instance, Bowen et al. (2020, p. 1254) recommend more cross-disciplinary “designers in the loop”. Further, the ‘right’ humans are needed for intersectional representation (UNESCO, 2020, p. 23) and socially responsible algorithms (Cheng et al., 2021, p. 26). This finding supports the imperative to find ways to support women in their AI careers to improve gender representation in AI development teams, the focus of this research.

In summary, a social perspective on the issue of AI bias is appropriate, given how many sectors and people are affected (Raisch & Krakowski, 2021, p. 33) and how most previous research has focused on the technical aspects only, which is a narrow approach that has drawn criticism (Whittaker et al., 2018, p. 11). The results of this phase support the importance of improving gender representation in AI development teams, which provided an impetus for solutions proposed in this research.

4.3. Phase 2 Findings

Due to the scarcity of literature and previous research, the theoretical lens and literature used to develop the conceptual model developed in Chapter 2 lacked application to AI. Thus, the conceptual model and the propositions needed confirmation and fine-tuning by WAIN experts in Phase 2. The objectives for this phase were, firstly, to explore WAIN experts’ opinions on the causes for a lack of women in the AI profession and the benefits of increasing gender diversity in AI; secondly to explore how WAINs support women in persisting and advancing in AI careers; thirdly, to explore the role of gender and professional identity in WAINs; and finally, to refine and verify the initial conceptual model from the perspective of WAIN experts.

The results of Phase 2 begin with the expert panel participant profiles and then proceeds with the major themes uncovered in the analysis process. Where significant, graphics of the themes have been included to illustrate the relative frequency of codes that emerged in the interview data. Direct quotes from participants have been provided in italics, to highlight examples of themes uncovered.

4.3.1. Participant profile

The participants were women in the AI profession who either represented the WAIN on a country or region basis or fulfilled another organisational role. All participants identified as women, and were of different ethnic origins and backgrounds, which is reflective of the overall WAIN leadership. There were seven participants in the expert panel, selected through purpose sampling as discussed in Chapter 3. Most participants were members of more than one network; however, all had leadership positions. Five of the seven experts interviewed were leaders or ambassadors of a specific country chapter of a WAIN, while six currently hold positions in the international leadership body of the WAIN. The participants were geographically widespread, with two from the USA, one from Africa, two from Europe, one from the Middle East and one from Asia. Four of the seven participants had backgrounds in computer science, three in psychology and one in marketing. This is shown in Table 2.

Table 2 Participant profile

Participant	Background	Region	Role
1	Computer Science	East Coast USA	Ambassador
2	Computer Science and Psychology	South Africa	Advisor, Ambassador
3	Marketing	India	Lead: social media
4	Psychology	West Coast USA	Editor, Partnerships, AI ethics
5	Computer Science, PhD AI	Sweden	Ambassador, Research
6	Psychology	Switzerland	Lead - Research
7	Computer Science	UAE	Ambassador; Lead: Partnerships

Table 2 reflects the wide variety of perspectives enabled by the diversity in the expert panel. An interesting and unexpected finding was the number of experts with psychology as a background. A social lens is useful when researching AI gender bias (Draude et al., 2019), which the field of AI ethics and psychology provides.

The main themes resulting from expert interviews analysis follow.

4.3.2. Reasons for lack of women in AI

The first objective for this phase included exploring WAIN experts' opinions on the causes for the lack of women in the AI profession, thus participants were asked to give their expert opinion on the issue, which were wide ranging and varied. Nine sub-themes emerged as reasons the experts held for why there is a lack of women in the AI profession, as depicted in Figure 18.

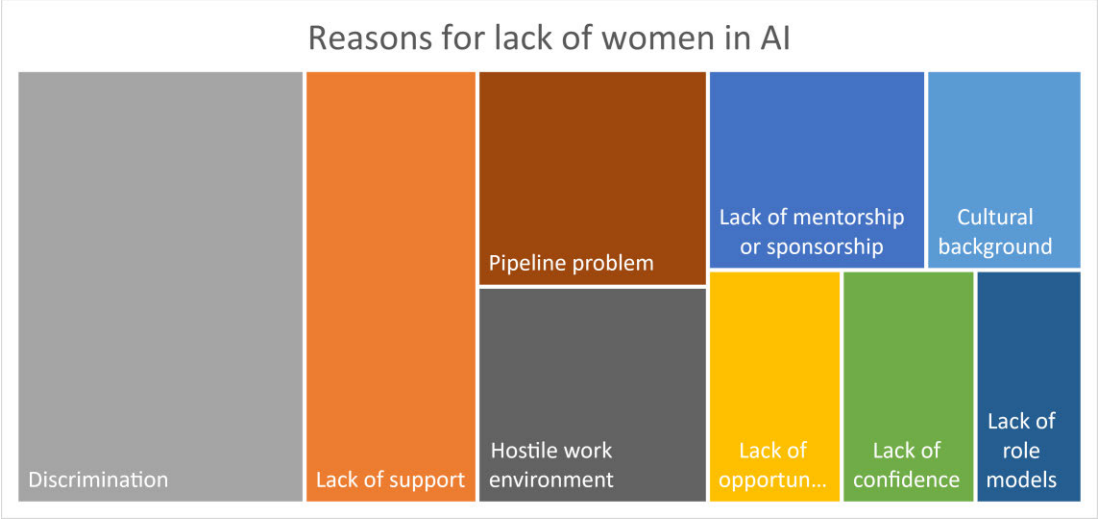

Figure 18 Reasons for lack of women in AI theme

Discrimination was cited the most, although it was nuanced, ranging from patriarchal work environments to pay discrimination to gender stereotypes. This finding is illustrated by Participant 2, who relayed:

> "*I remember very evidently that I had more qualifications than the male counterparts and I remember how often I was the only one asked to take minutes, to go and make coffee".*

A similar sentiment was expressed by Participant 4, who pointed to general gender discrimination in society:

> "*Just like every other field dominated by men, for some reason, and societal problems and [the way] society is set up*".

Lack of support was another prominent sub-theme the participants felt strongly about, as Participant 4 stated:

> "*Unless we change the system, I don't think it's going to be a supportive environment for women*".

Lack of support includes a lack of peer support, respect, encouragement and recognition. As Participant 1 said:

> "*Just in the quantity there were many more men than women and so they had way more support and way more encouragement, in a sense, from each other. They would have these study groups and they would do programming together and do their AI projects together*."

Lack of support was related to as a reason for a pipeline problem – which points to the lack of a talent pool from which women can be drawn and promoted (Young, 2021, p. 8). This was illustrated by Participant 3, who explained:

> "*So it starts at the grassroots level and then sometimes they're not even encouraged by family".*

Participants 5 and 7 suggested that:

> *"Once you're within that pipeline it's already skewed"* and *"I know there's a problem with the pool or the pipeline. There's a serious problem with that."*

More than lack of support, some participants encountered hostile work environments. Participant 1 noted that the hostile work environment in her workplace made networking at work impossible, while Participant 5 explained:

> *"It's very hostile conditions, and also it's a lonely place, you're not really finding collaborators, you don't find funding."*

Many of the sub-themes are closely related, such as lack of mentorship, sponsorship, role models and lack of opportunity. These sub-themes recurred throughout the research. For example, Participant 1 explained:

> "*Having someone to coach you or to sponsor you in some sense in the workplace for more opportunities so that's much less for women than it is for men."*

Participant 4 explained regarding role models:

> "*That is a roadblock for everyone like when we don't see someone who looks like us in the field, we naturally try not to go into that field."*

Lack of mentorship is a reason for some participants feeling a lack of support and a hostile work environment, as Participant 2 explained:

> *"It's also on the coaching and mentoring side of things, a lot of the time [it] was "okay, what are you kind of doing here?". You kind of really felt like you didn't belong, or you had to be one of the guys."*

Cultural background and hostile work environment were also intertwined with the discrimination and lack of support themes. This is illustrated by Participant 1, who explained:

> "*One is the stereotypes embedded in so many cultures where women either aren't even allowed to work or there are certain professions that aren't deemed fit for them and so it inhibits the number of possibilities… again with respect to stereotypes, again with respect to discrimination and with respect to people not hearing them and not valuing them as an expert in the field".*

Overall, most of sub-themes related to reasons for feeling discrimination, of which lack of support was the main contributing factor. This could be related to why the participants were so active in the WAIN.

4.3.3. Benefits of including more women in AI

Part of the first objective for this phase also included exploring the benefits of increasing gender diversity in AI. If there were to be more representation of women in AI development teams, the expert panel agreed on an inter-related set of positive consequences, including increased diversity of opinions and better-designed and less-biased solutions. Figure 19 shows the beneficial implications of more women in AI.

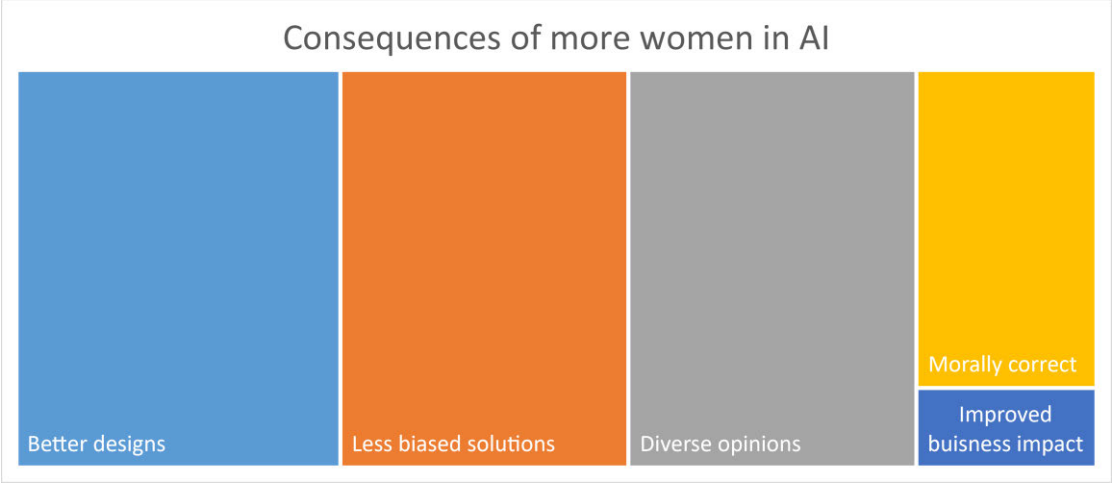

Figure 19 Benefits of more women in AI Theme

The majority of the participants identified better design of AI solutions as the key benefit. Participant 4 explained the reason why:

> "*Woman in general see everything more holistically and take more holistic approach to every problem. They don't see a problem in a vacuum. They don't see a problem in isolation from the environment. Somehow that is my general concern whenever I talk to the engineering community, the AI community which is mostly dominated by men - they see a problem, whatever the problem they have at hand, they see it as separate from ecosystem, from the larger ecosystem. And when you talk to women, maybe because how society has programmed us to live within an ecosystem, to take everyone's considerations, everything we do, whether it is at home or at work we somehow naturally have this ability to see everything as part of an ecosystem".*

The 'big picture' perspective that diverse opinions provided by women provide in technical projects was also reflected by Participant 3:

> *"They bring their own voice, they bring a different personality, they bring a new way of thinking, a fresh perspective".*

Participant 2 also reflected on the benefits of diverse opinions leading to better designs:

> "*…it is the ability to adapt, the ability to see things a little bit more holistically you know, bringing a fresh pair of eyes just adds the diversity element".*

Less biased AI solutions was a benefit of increased gender representation in AI development teams, that all participants expressed. The reason for this thinking was explained by Participant 3:

> "*If your ideas are not being portrayed in the code, for example, if it's only a man coding, he would think from his perspective and all his unconscious bias, which comes from societal bias actually, is portrayed in his coding".*

Participant 7 summed up what most participants felt:

> *"And how do you prevent bias from creeping into our solutions … having the right people at the strategy table."*

More women in AI teams is even more important for unbiased solutions when the AI solution has far reaching consequences. As Participant 6 put it:

> *"If we're talking about an application that is used in in the field, in the greater society, then representation is probably most important since we want to make sure that there're fair outcomes."*

Better designs from diverse opinions also creates better solutions and results for business:

> "*Diverse opinions always, always help to form any product in any space much more holistically. It caters for a lot more people, you know … it helps to catch all the blind spots."*

Participants provided two specific examples of less biased designs and better results from more women in development teams:

Participant 4:

> *"I don't think women would actually look at a language chatbot as just a language chatbot problem. They would not see facial recognition as just a facial recognition problem – 'just add a few more black faces and we'll solve it' - women would never see it that way, they see it as a whole large ecosystem."*

Participant 2:

> *'If I can give an example, in the Metaverse, there's already a groping problem. I believe that if there were women in the testing team or if they were listened to, we could have had solutions to this problem already."*

An interesting sub-theme was that the experts considered it morally correct to have more diverse AI development teams, for example, Participant 1 stated:

> "*It's just the right thing to do – to have everyone's voice heard. It's the right thing to do to have everyone feel valued and included".*

Overall, the participants provided solid arguments for the benefits of more women in AI, which linked back to the need for more support. Such support can be found in the form of WAINs.

4.3.4. Benefits of WAINs

An objective of Phase 2 was to explore how WAINs support women in AI careers. One element of this was to gain the participants' views on the benefits of WAINs. Three primary benefits of WAINs emerged from this research. These are firstly, the social support received through connections made in the network; secondly, opportunities provided by the network and lastly, role models and mentorship facilitated by the network.

Social support from networks:

The experts indicated that social support was a key benefit of network membership they have experienced personally and had heard from member feedback. This theme was a surprising finding that had not emerged in the original model based on the theory and literature. Figure 20 below shows the sub-themes that emerged from the expert panel related to Social Support.

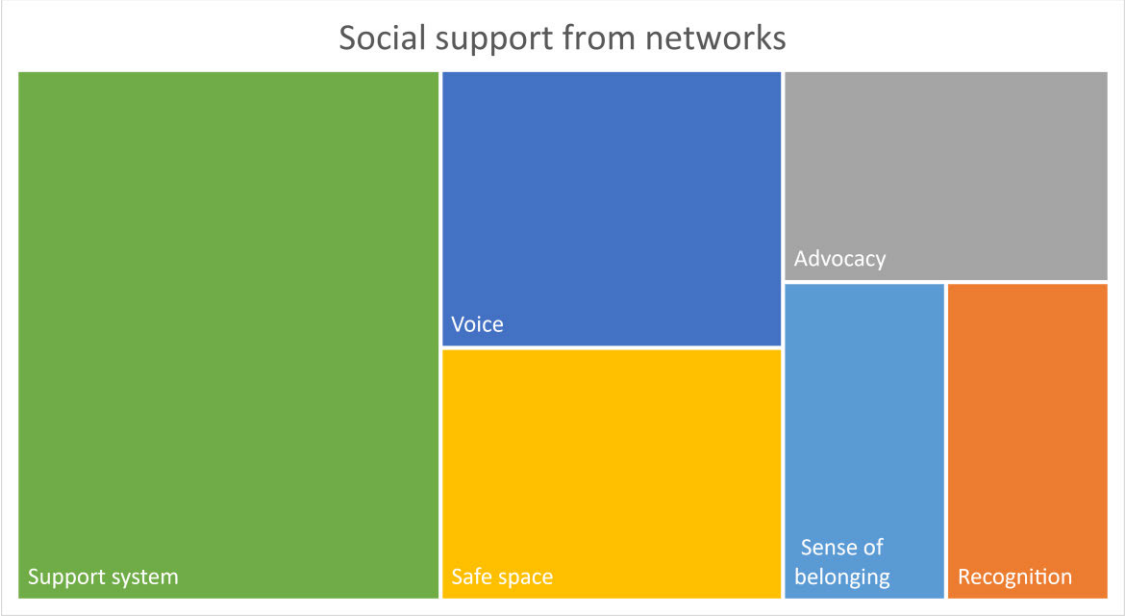

Figure 20 WAIN social support theme

One reason this theme may not have emerged previously is the unique context that networking during COVID-19 provided. For example, in the context of Covid-19, one participant explained:

> *"Hope and encouragement that we are all going through it and it's something that's inevitable right now but it's like the end of the tunnel - we see light, it's coming, but we have each other while we're walking through the tunnel."*

Numerous references were made to a sense of belonging and sisterhood and psychological safety provided by the network. These are intangible benefits, as Participant 4 explained:

> *"I think the main service is intangible, here, I would say it is being part of a community, part of sisterhood".* Participant 1 added: "*The ability for having community, so you know, situations where friends become family kind of scenario."*

The network provides the support system that is not found within organisations – aligning with the findings about why there is a lack of women in AI. For example, Participant 6 stated:

> *"I think you can benefit from knowing that there are these women out there, but they're just not in my company at the moment, or in my team. So I still have a kind of a plan B safety net".*

Similarly, allowing women to advocate for other women, to be seen, to increase their visibility and voice, is an intangible benefit of WAINs. In fact, it was suggested that the lack of women's 'voice' at AI events was a driving factor for the founders to create the WAI network. Participant 5 explained that members "*get a lot of, you know, support and advocacy*", while Participant 1 suggested that the WAIN gives "*you the platform to represent yourself, to make yourself visible to the larger world*". It was also clear that the participants felt the network encourages members to "*ruthlessly advocate for themselves*" and provide sponsors "*who can actually advocate for you*".

Recognition for skills and achievements in the AI profession was cited as one of the benefits of WAINs as it provides women with accolades they can use to further their careers and position in the profession:

> "O*ne of benefits of Women in AI is to help anybody be more visible, be more active, be more eminent in their careers in AI.*"

Recognition includes formal awards and informal recognition:

> "*We can showcase their skills and you know, take an award for their amazing achievement. So I think that is something that is pushed and you get it out of a community. You know, you feel recognised amongst your peers.*"

The participants' emphasis on the significance of social support within WAINs is evident from the preceding discussion. Social support can be distinguished from more instrumental support, the focus of the next theme.

Opportunities provided by the network:

The participants expanded on seven main opportunities presented by the network in support for members' careers, as presented in Figure 21.

Figure 21 Opportunities provided by the WAIN theme

Multiple learning opportunities are provided by WAINs, sourced from events, workshops, mentors, peers, and courses. Formal resources mentioned were boot camps, masterclasses and AI projects, for example:

> *"We had a boot camp on robotics or machine learning or a particular section of AI."*

Participants also stressed that the network provides opportunities to learn soft skills, often acquired from volunteering. For example:

> "*Learning more skills and meeting more people who have a wider range of skills than you do or have a different set of skills than you do always helps you have a more holistic bucket, that you can present for your next promotion or your next job."*

Speaking and volunteering opportunities at events increased members' eminence and profile in the AI industry, furthering their career prospects and skills. For example:

> *"When you speak at events, you get the opportunity to meet amazing people again and to show your talent maybe or the work you've done in the past and I think this is the way of also getting recognised."* Additionally, by volunteering "*you can be a leader in quite a prestigious*

team" and "*you can learn a lot and especially from your peers because they are the best of best in the industry.*"

Career opportunities, be it help in starting your own business or finding a job, were also identified by the participants. Specific formal programs for startups are available in the WAIN, including funding and mentor opportunities. Participant 4 was a recipient:

> *"I also founded a startup; an AI start up. So I was part of their Accelerator program.*"

The accelerator program was explained as:

> *"…where women who are working in AI and have this entrepreneurial spirit, they want to like, go ahead with their idea and start their own businesses – startups, they are trained over a period of six months or eight months from industry experts and they are given help to start off."*

There are also formal job opportunities provided by job boards on the WAIN where opportunities are posted. Informal opportunities are also available, for example:

> *"I've heard so many stories where you know, a women got connected with someone and then they were offered a job because they were really good. I think so many job opportunities can be found."*

Connections to large companies through sponsorships leads to career opportunities, as explained by Participant 7:

> *"I've heard lots of these companies say well we have to connect with women in AI, we have to be intricately involved because we need those contacts. We need to know who the women are who can fulfil these positions, there's just a lack of it and that's why I think Women in AI is really going to be a strong player going forward."*

A less obvious opportunity identified by the experts can be described as self-promotion, for example:

> *"…you are your own brand, you're selling yourself as well*".

Additionally, the network provides opportunities to both find and participate in new research:

> *"'I've heard of people coming together and writing books or research papers, the possibilities have just been phenomenal."*

Overall, opportunities offered by WAINs were varied and significant from an instrumental career perspective, including gaining skills, speaker offers and job opportunities.

Mentors and role model support:

The initial conceptual model specified two forms of support: mentors and role models; however the expert participants identified two additional roles – sponsors and allies. However, mentors and mentorship came up by far the most, as illustrated in Figure 22 below:

Figure 22 Mentor and role model support provided by a WAIN Theme

The importance of relationships was illustrated by Participant 1:

> *"Form a relationship with someone who is probably two steps higher in the career ladder, which is always helpful because you get more perspective, and you get someone who can tell you about the opportunities and they can probably even advocate for you."*

Mentorship offers opportunities for members and is one of the most impactful programs the WAIN offers:

> *"I think accessibility to a student in the middle of a rural area in Africa becomes key. So, if we could get that mentorship to that person that's where we're starting to make impact."*

Participants also expressed the long-term benefits of formal mentorship programs offered by the WAIN from a social support perspective:

"Even though the mentorship may be on a short-term basis like temporary, three months, six months, it's still a whole valuable experience and you do maintain a lifelong relationship with your mentor."

And from an opportunities perspective*:*

> *"Mentorship is huge, when we did the mentorship program it really opened a lot of doors for people who were involved in it. So, we find people at a very senior level and match them with wherever the person enrolled is in their career."*

Participant 7 has benefited personally from mentorship:

> "*I normally have about 5 mentors at a certain point in time for various reasons, various areas of my life in my career and that always helps tremendously to help build that- they will introduce you to more people."*

The importance of role models in the network was emphasised by several of the experts, as an element of social support:

> *"Role models is huge, right? I mean, that's the whole point of all of these communities, right? It's the role modelling that helps you. It's the courage, to see other people go where you know you are trying to go."*

Two additional roles emerged that were not explicitly identified in the conceptual model: sponsors and allies. Both roles offer social support and provide opportunities and resources for WAIN members:

> *"Sponsorship and allies who can advocate for them can bring them more opportunities, can make them feel respected, help them and support them when they need that support is something that is missing for women."*

Allies were described as "*those that can support your careers and sort of amplify them."* Both sponsorship and ally roles arose in the context of supporting women in career advancement:

> *"Through the network you can find sponsors who can actually advocate for you when there's an opportunity that comes up to them and they*

can see that you're a great fit for it and they can set you up with that opportunity so that is one way the network can help you advance in your career."

Overall, the participants stressed that mentors, role models, sponsors, allies and other advocacy roles provide members with social support and opportunities and resources. These elements should be part of the new construct – social support and a more extensive opportunities and resources construct.

Gender and professional identity

The conceptual model included gender identity and AI professional identity as two elements that may moderate the relationship between networking and careers, therefore one of the aims of this phase was to explore the role of gender and professional identity in WAINs. As one participant explained the concepts:

"I think the gender identity is probably on the softer side, whereas the AI being part of your career identity is more the hard, 'yes this is who I am', you know, this is what defines my thinking and my career aspects."

While the experts felt that both concepts were likely among members, they did not see them as factors that would play a role the behaviour of members or their membership. Rather, these would be reasons for joining the WAIN. For example, Participant 3 suggested "*Spirit and the passion is shared together here and that's very inviting"* when asked about professional identity.

While Participant 2 explained:

"I think that the gender plays a part in terms of us entering the network right, so yes, we see that. I kind of fit in that category and then go explore. But once you're in it , it's about curiosity, I think curiosity drives a lot of what you get out of a network".

Similarly, Participant 1 explained that members with a strong gender identity would benefit but that "*this is not to say that those who do not identify so strongly would not get the same benefits out of the network."* In addition *"responsibility falls on the community so that ever is part of the community does feel passionate about being in AI"* indicating that strong AI professional identity is not required of members.

Overall, the experts did not subscribe to members' personal identities as being significant factors in how they networked. Rather, gender identity was a reason for joining the network, and having a strong AI professional identity is necessary to persist in AI.

4.3.5. Networking behaviour

The conceptual model proposed three stages of networking – building, maintaining and leveraging. Regarding network building behaviour, participants suggested being proactive in connecting with other members, communicating using forums provided by the network, and participating in events put on by local chapters. For example Participant 5 explained that for members to build their network they need to

> *"Go to more events, talk to people, not just keep to themselves, actually DO the networking part."*

Participant 5 suggested attending conferences and events hosted by the WAIN and connecting with the hosts:

> *"Try to connect with the ambassador as well as the core team members who themselves can be a very good place to start networking."*

Leveraging behaviour can have benefits in the workplace, as Participant 1 explained:

> "*If you are facing discrimination or you're facing coworkers that you don't really enjoy working with, how do you navigate doing that? So you leverage your network to get support for that.*"

Additionally, leveraging behaviour can include practical help for interview preparation or introduction to career advancement opportunities, as Participant 5 explained:

> "*You can start to leverage the network to get the things that you want - perhaps a better position, perhaps learning more within AI."*

Regarding overall networking behaviour, the experts felt that COVID-19 had increased networking behaviour, the ensuing lockdowns and lack of physical networking forced many networks and networking events to become virtual, facilitating participation by more remote members and allowing for global networking:

> "*We've been very fortunate with the pandemic because we've had a lot more access, you know, than we normally would have"* And "*when the pandemic started everyone was all open to yes, drop me a message …. was really great and just connected quite easily*."

By networking more, many of the benefits explained in the themes above, such as opportunities, can be gained, for example as Participant 5 explained:

> *"See opportunities come your way. You have to be aware of that, that every time you are doing something you are also making sure that there is an opening the door to newer opportunities, newer things that you have not explored yet."*

Most of the participants urged active participation through volunteering, suggesting this was the beneficial networking behaviour. For example, Participant 6 emphasised:

> *"The moment where you volunteer and you know do more concrete things and more officially and publicly then you have the maximum greatest benefit."*

Likewise, Participant 3 explained:

> "*As a volunteer, you can learn a lot and especially from your peers because they are the best of best in the industry and just being around them and having that five minutes, I think is amazing."*

Network leveraging, building and maintaining behaviour all overlap. There was no clear distinction between the three concepts by the participants. Rather, they stressed elements such as communication, being important networking behaviour overall:

> *"I think communicate. They should really, really go out there, because I see that there are so many amazing women that you could, you can leverage them."*

Another common element across all three stages is being consistently active. As Participant 6 stated "*you've got be very active and proactive",* reiterated by Participant 2 who stressed "*consistency in your actions*" as positive member networking *behaviour.* Effort and proactive participation are therefore key networking behaviours as Participant 2 put it: "*The more you do, the more you get back*."

Thus, although the conceptual model differentiated between the dimensions of building, maintaining and leveraging overlap, the experts emphasised the importance of overall networking behaviour and suggested members should be active and consistent in their networking behaviour to get the most out of their membership.

4.3.6. Career persistence and advancement

Two constructs from the conceptual model are career persistence and advancement. The participants were asked how WAINs can assist members in advancing and persisting in their careers in AI. The thoughts of the experts interviewed were predictably related to themes already discussed. For example, lack of career persistence was ascribed to a lack of mentorship, allies, a hostile work environment, lack of support, encouragement and role models:

"*It's very hostile conditions, and also it's a lonely place, you're not really finding collaborators, you don't find funding".*

Similarly, themes already explained arose for career advancement - opportunities, resources and support facilitated by networking. This finding is summed up well by one participant:

"*Join communities. This is almost like a no-brainer, and you get so, so much out of it. The benefits are just tremendous, and you can start small - just join the Slack channel, read through whatever is going on there, research which women makes most sense to you to connect with - and I haven't seen any woman in that community that does not respond with such kindness and wisdom and help. And you can get your job offers there. If you're at the stage where you want to become more eminent, there's even places where you can see what type of speaking engagements there are or opportunities. And your education is there, I mean we have fantastic free education that we list there in the community*".

The international nature of the WAI network means that support and encouragement to persist in the field is necessary, as Participant 7 said:

"I know the latest stats that I last saw was 26% women in data and in AI, it also varies per region like the APAC region only has 16% women… in China it's less than 10% and so that it is quite a worrying thing… the network really helps you to find these different pieces that you need to stay."

Regarding how the network can assist women in remaining in AI, Participant 1 suggested:

"*Try and catch those people who are trying to leave and understand why they're leaving and then to provide the resources to help them.*"

Participant 4 suggested networks can assist women in persisting in the field though different levels and types of support:

"Emotional support, and moral support, but [also] some hard pointers and skills … "Here is what you need to do, here is how you should handle that manager, this is how you should handle this project".

Similarly, Participant 6 pointed to different types of skills the network can assist with, both of which are needed for women to advance in the AI field:

"The most important thing … is the psychological but also the technical support. So you can ask tech questions but obviously also have the psychological support as your safety net and people, you can talk to people you like".

Some specific resources that can help women persist and advance were suggested by Participant 3:

"*Upskill, attending events, funding opportunities, research opportunities, speaking opportunities*".

Participant 7 suggested the following ways WAINs can assist women in advancing in their AI careers:

"It really helps you with your with your ability to speak, your ability to communicate, it helps you with your eminence, with just having confidence, this is tremendous. And have that visibility, you know if you manage to do a talk well and it's recorded, it's there, it's on YouTube and you can show it to potential employers and so on, and all people see it and they want to work with you because they see the work that you're doing".

Overall, the participants described seeking support, joining communities and upskilling as important devices for women in persisting and advancing in theory AI careers.

A summary of the themes is provided in Table 3 below.

Table 3 Themes resulting from analysis of expert interviews.

Results of thematic coding		
Representation of women in AI	Reasons for a lack of women in AI	Discrimination
		Lack of support
		Pipeline problem
		Hostile work environment
		Lack of mentors/sponsors
		Lack of opportunity
		Lack of confidence
		Cultural background
		Lack of role models
	Benefits of more women in AI	Better designs
		Diverse opinions
		Less biased solutions
		Morally correct
		Improved business impact
		Diverse opinions
Benefits offered by WAINs	Social support	Support system
		Voice
		Safe space
		Advocacy
		Recognition

		Sense of belonging
	Opportunities	Learning opportunities
		Speaking opportunities
		Volunteering opportunities
		Start-up opportunities
		Job opportunities
		Promotion opportunities
		Research opportunities
	Mentors and role models support	Mentors
		Role models
		Sponsors
		Allies
WAIN members' Individual identities	Personal identity	Gender identity
		AI professional identity
WAIN members' networking behaviour	Networking behaviour	Network building
		Network maintaining
		Network leveraging
WAIN members careers	Career stages	Career persistence
		Career advancement

4.3.7. Discussion of Phase 2 results

This research phase sought expert opinion on the conceptual model devised to explore the relationship between WAINs and women in AI careers. The specific objectives for Phase 2 of the research were met and are discussed below.

The first objective was "*To explore WAIN experts' opinions on the causes for a lack of women in the AI profession and the benefits of increasing gender diversity in AI*". The experts suggested that women in AI experience discrimination, a hostile work environment, lack of opportunity, support, mentorship and role models. These reasons for the lack of women in AI are corroborated by literature (e.g. Osoba & Welser, 2017; Roopaei et al., 2021; Saka, 2020). Obukhova and Kleinbaum (2022, p. 31) contend that women avoid jobs where they expect hostile work cultures and "gender-based obstacles". Some issues raised, such as "groping in the metaverse", are unlikely to be addressed through more inclusivity in development teams, but WAINs could put pressure on policy makers to address such problems. From the expert WAIN leaders' perspective, more inclusive development teams will create better AI solutions through better design and, ultimately, better business results. Further, this will have positive societal consequences, as supported by Roopaei et al. (2021, p. 497): "the importance of women's input cannot be excluded from AI development. Women will ensure that the AI industry has a diverse perspective and will encourage innovative ideas and outcomes of AI technology, and its considerable effect on day-to-day lives." Cerit et al. (2020, p. 1) suggest increased participation by women will reduce gender discrimination in general. Similarly, Whittaker et al. (2018, p. 42) explain "Furthermore, it is long overdue for technology companies to directly address the cultures of exclusion and discrimination in the workplace. The lack of diversity and ongoing tactics of harassment, exclusion, and unequal pay are not only deeply harmful to employees in these companies but also impacts the AI products they release, producing tools that perpetuate bias and discrimination.".

The second objective was "*To explore how WAINs support women in persisting and advancing in AI careers*". The initial model highlighted learning opportunities as an important network benefit. The expert panel suggested opportunities extending beyond learning to include many other opportunities and resources provided by the network to assist members in persisting and advancing their AI careers. The initial model also singled out mentorship and role models as benefits of WAINs. The expert panel agreed

and proposed sponsors and allies as advocates for women in AI. This view is corroborated by Porter et al. (2023, p. 14), who suggested that sponsors can increase women's visibility and job choices. Allies can be equally important, contends Roopaei et al. (2021, p. 498) in proactively increasing the representation of women in AI. A broader, new construct was revealed from the analysis – that of social support. While networks are known to provide social and emotional support (Tasselli & Sancino, 2023, p. 171), the original theories on which the initial conceptual model was based did not suggest a role for this construct in the relationship between networking and career persistence or advancement. However, the expert panel exposed various social support concepts, as shown in Figure 23. The COVID-19 pandemic was suggested as a reason for the importance of social support, evidenced by the growth in WAIN membership, with international online collaborations and networking (WAI, 2021). Overall, the experts agreed that social support and opportunities provided by WAINs are key to supporting women's careers in the AI field, aligning with the research objective.

The third objective was "*To explore the role of gender and professional identity in WAINs*". Interestingly, the role of gender identity was deemphasised as many of the experts did not feel it was as pertinent as the original model suggested, where gender identity was proposed to moderate the relationship between networking behaviour and career persistence and advancement for women in AI. Instead, gender identity plays a role only in joining the network as women seek gender-relevant network resources (Obukhova & Kleinbaum, 2022, p. 31). Similarly, the participants agreed the role of AI professional identity would not impact women's networking or membership in the WAIN. Therefore, the construct of AI professional identify was subsumed into the construct of career persistence, in line with Dobrow and Higgins's (2005, p. 569) finding that professional identity is part of subjective career success. Further supporting this decision is the fact that the scale measuring career persistence includes an item about being emotionally attached to the AI profession.

The final objective of Phase 2 was "*To refine and verify the initial conceptual model from the perspective of WAIN experts*". From the initial conceptual model, the following adaptations to the propositions arising from Phase 2 were made, based on reasoning provided in expert opinions discussed above:

- Gender Identity was removed as a moderator.

- Professional Identity was subsumed into Career Persistence.
- Learning Opportunities was expanded to include more types of opportunities and renamed Opportunities and Resources.
- A new mediating variable – Social Support was added.
- Mentorship and Role Models were subsumed into the new construct of Social Support.

The result was a testable model which provides the starting point for Phase 3 of the research. The final model suggests that the more networking behaviour displayed by WAIN members, the more likely they are to persist and advance in AI careers. Further, social support and opportunities and resources provided by the network will mediate that relationship.

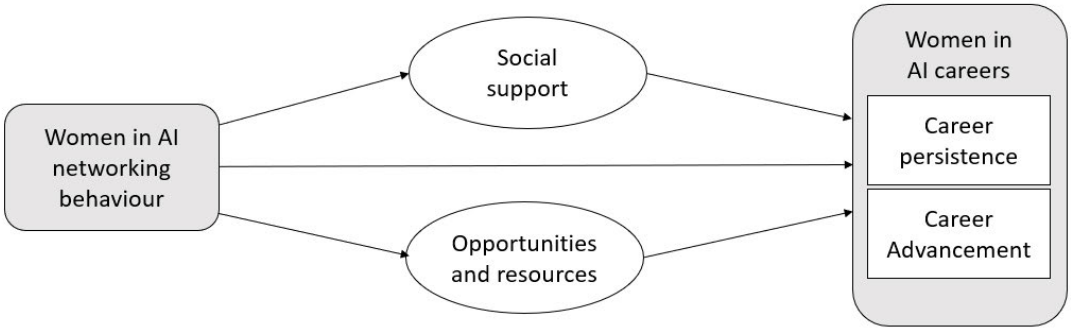

Figure 23 Revised conceptual model

Each variable in the model and a suitable scale to measure the variable are discussed next, including hypotheses arising from the model to be tested in Phase 3.

The model in Figure 23 above depicts the *networking behaviour* displayed by WAINs as the independent variable. Networking is a proactive behaviour by people intending to optimise their career potential, outcomes and success (De Vos, Akkermans, & Van der Heijden, 2019, p. 133). Fryczyńska and Ivanova (2019, p. 212) were among a variety of researchers who found a link between networking and advancing careers. However, there was little evidence of this for formal women-only networks such as Women in AI. The networking behaviour scale developed and validated by Wolff and Spurk (2020, p. 277) was adjusted to fit WAINs.

Members of WAINs are typically in the profession already; thus, the stages of career persistence and career advancement are included in this model. Armstrong et al. (2018, p. 3) found lack of networking is a barrier to career persistence and advancement. *Career advancement* is measured by the members' satisfaction with the success they have achieved in their careers, based on the scale developed by Spurk et al. (2011, p. 326). Career persistence refers to WAIN members remaining in the AI profession, with affective career commitment scale forming the basis of the measure (Brooks et al., 2015, p. 23). Career persistence and advancement are the dependent variables in the model, and this remains the same as the initial conceptual model. The first two hypotheses are therefore:

> *H_1 = The more networking behaviour displayed by women in AI, the more they will persist in their careers in AI.*
>
> *H_{01} = There is no relationship between networking behaviour displayed by women in AI and their persistence in their careers in AI.*

> *H_2 = The more networking behaviour displayed by women in AI, the more they will advance their careers in AI.*
>
> *H_{02} = There is no relationship between networking behaviour displayed by women in AI and advancement in their careers in AI.*

Social support and opportunities and resources are depicted in the model as mediating variables between networking behaviour and women in AI careers. *Social support* refers to the emotional and personal support provided by the network and is measured by the social provision scale by Steigen and Bergh (2019, p. 29). The next two hypotheses are:

> *H_3 = The positive impact of networking behaviour on women in AI career persistence is mediated by the social support offered by the network.*
>
> *H_{03} = There is no social support mediation relationship between networking behaviour and women in AI career persistence.*

> *H_4 = The positive impact of networking behaviour on women in AI career advancement is mediated by the social support offered by the network.*

H_{04} = There is no social support mediation relationship between networking behaviour and women in AI career advancement.

Opportunities and resources range from education on AI issues and technology, to career and personal development, to learning about job opportunities and research. Hirschi et al. (2018, p. 342) considered various constructs under the umbrella term career resources that can be applied to this study, such as learning and career opportunities for WAIN members. The large publicly available WAINs offer numerous opportunities for members, such as short courses, events and hackathons (WAI, 2021). This mediating variable can be measured by the career resources and learning scale developed by Hirschi et al. (2018, p. 342). The following hypotheses are proposed:

H_5 = The positive impact of networking behaviour on women in AI career persistence is mediated by the opportunities and resources offered by the network.

H_{05} = There is no opportunities and resources mediation relationship between networking behaviour and women in AI career persistence.

H_6 = The positive impact of networking behaviour on women in AI career advancement is mediated by the opportunities and resources offered by the network.

H_{06} = There is no opportunities and resources mediation relationship between networking behaviour and women in AI career advancement.

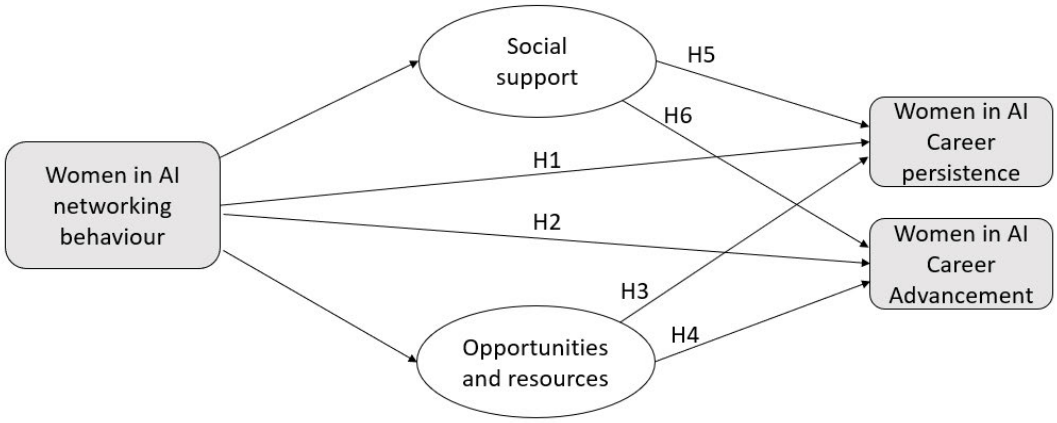

Figure 24 Final model after Phase 2

Overall, the results of Phase 2 provided a deeper understanding of WAINs and their members and strengthened the conceptual model developed from literature in Chapter 2. This resulting model was then tested in Phase 3.

4.4. Phase 3 Findings

The main objective of Phase 3 was to determine the relationships between networking behaviour and career persistence and advancement. The model was refined in Phase 2 of the research, based on an in-depth qualitative analysis of interview data from a panel of experts and leaders in WAINs. The hypotheses to be tested in Phase 3 were derived from the Phase 2 model. The model illustrates a potential direct relationship between WAIN member networking behaviour and their careers, or indirectly through support and opportunities and resources offered by the network. The impact could relate to the members either persisting in their careers or successfully advancing in their careers in AI.

The results of the analysis are presented next, starting with the sample profile, then the descriptive statistics and, finally, the testing of the hypotheses through structured equation modelling.

4.4.1. Sample profile

The demographic profile of the sample (N=206) is shown in Table 4 below, with a detailed table for each variable provided in Appendix D.

Table 4 Demographic profile

N=206	**Frequencies (percentages)**					
Age	Under 21	21-30	31-40	41-50	51-60	>60
	2 (1%)	87 (42.2)	75 (36.4%)	33 (16%)	7 (3.4%)	2 (1%)
Ethnicity	Asian	Black	Hispanic, Latino or Spanish origin	Middle Eastern or North African	White	Other/prefer not to say
	60 (29.1%)	25 (12.1%)	12 (5.8%)	15 (7.3%)	83 (40.3%)	11 (5.4%)
Highest Education	Secondary school not completed	Secondary school completed	Tertiary completed	Post-graduate completed		
	0 (0%)	10 (4.9%)	50 (24.3%)	146 (70.9%)		
Gender Identity	Female	Male	Prefer to self-describe	Prefer not to say	Other	
	198 (96.1%)	4 (1.9%)	2 (1%)	1 (0.5%)	1 (0.5%)	

Age

The majority (78.6%) of women in AI network member respondents were between 21 and 40 years (n=206), with 43% being younger than 30 and only 1% over 60 years old, reflecting the recency of AI as a profession.

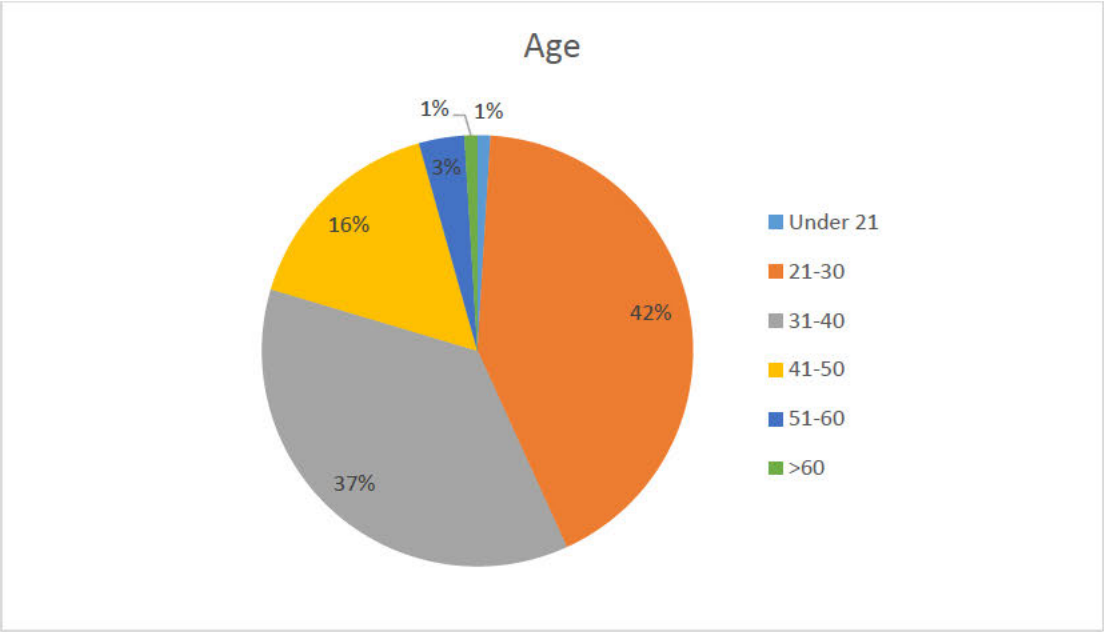

Figure 25 Frequency distributions for age group

Ethnicity

All ethnicities were represented, with many of the respondents identifying as white - (E.g., German, Irish, English, Italian, Polish, French, etc.), at 82 (40.3%) or Asian (E.g., Chinese, Filipino, Asian Indian, Vietnamese, Korean, Japanese, etc.) at 60 (29.15%) as shown in the figure below.

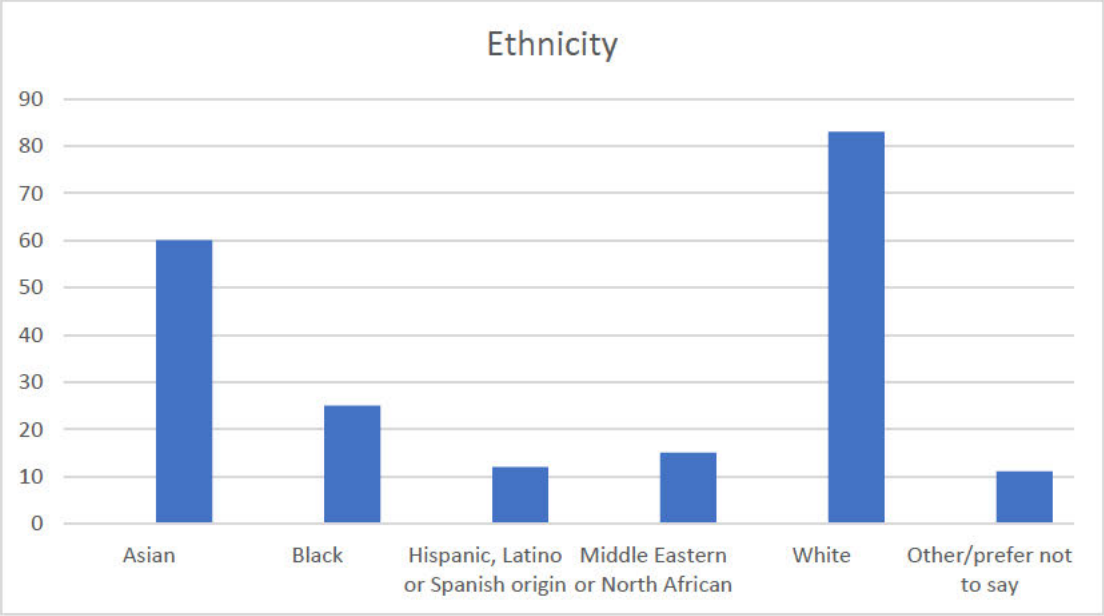

Figure 26 Ethnicity

Gender identity

Of the ten options provided, 96% of respondents identified as female, which is not surprising given the network is named Women in AI, however there were some variations as depicted in the chart below. With the overwhelming number of respondents identifying as women, the use of the word 'women' in the final model was retained.

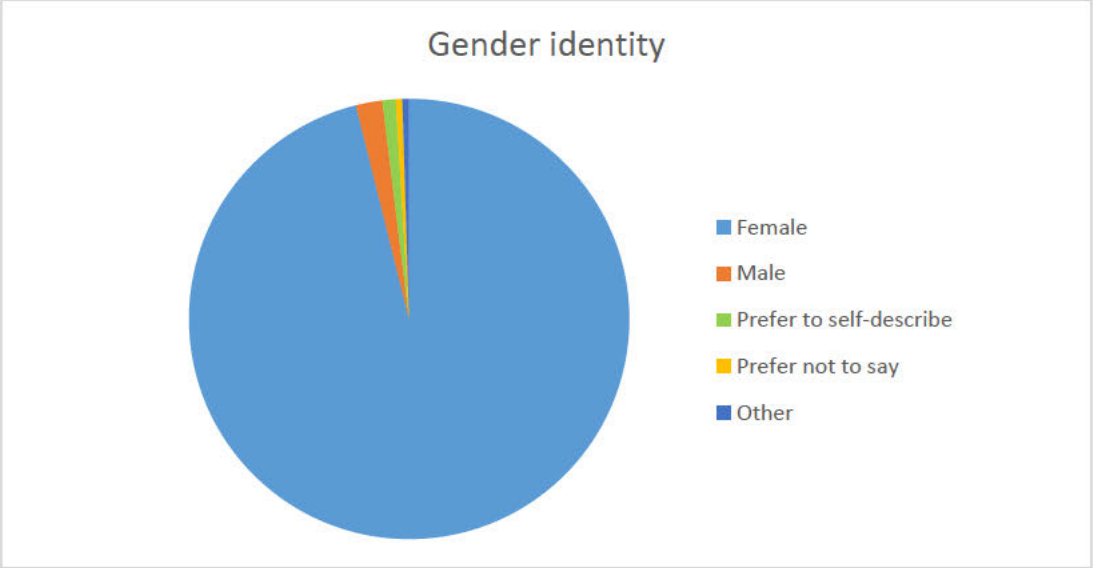

Figure 27 Gender identity

Education

Over 70% of the respondents had a post-graduate qualification, and all had completed secondary school, indicating a high level of education among participants, perhaps indicative of the nature of AI work and the profession. However, it is still surprising the number of post-gradates the sample contained.

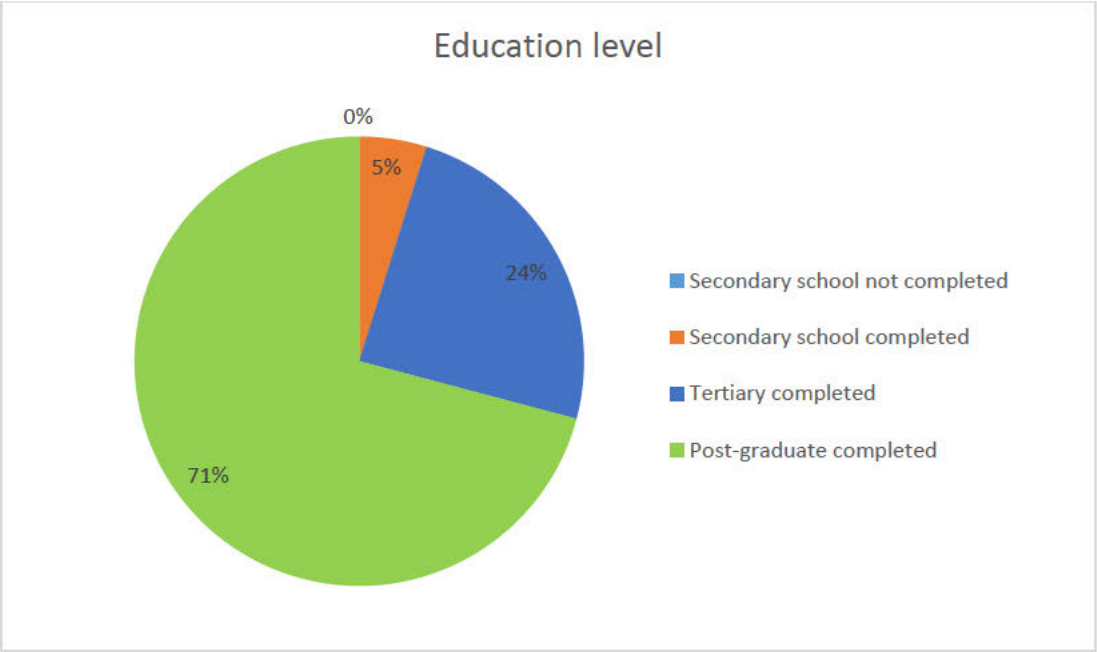

Figure 28 Education Level

Most respondents had an engineering or IT educational background (53%), as expected in the AI profession. However, the variety of backgrounds was interesting, from economics and management (8.3%) to natural science (6.3%) and philosophy (2.5%) - reflective of the interest in the field. Notably, 10.7% had more than one educational area, with some participants having 3 degrees in fields as varied as arts, business and computer science.

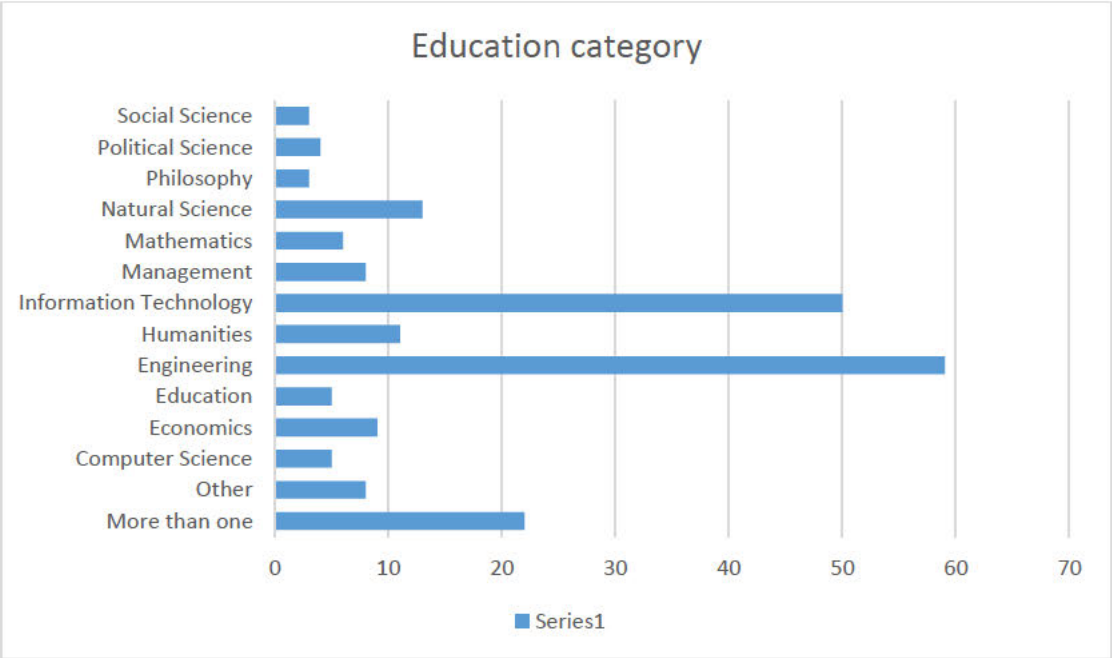

Figure 29 Educational category

Country of residence

The respondents represented 40 countries reflecting the international nature of the WAIN, with 27% residing in North American countries and 38% in European countries. The remaining 35% represented countries in Asia and Africa.

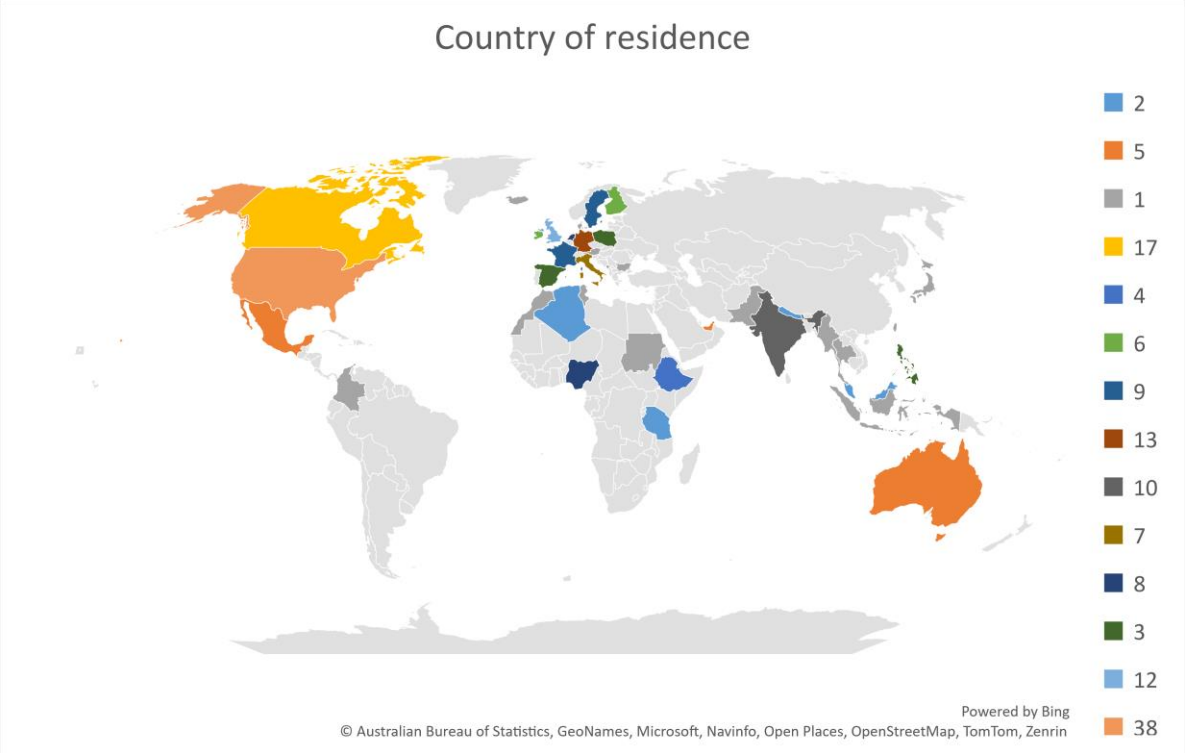

Figure 30 Country of residence

Having established the respondents' demographic profile, the next section provides an analysis of the respondents' careers in the AI profession.

4.4.2. WAIN member careers

Table 5 below provides an overview of descriptive statistics related to the WAIN members' careers.

Table 5 Women in AI network's careers

N=206	Frequencies (percentages)					
Working experience	<6 years	6-10	11-15	16-20	21-25	>25 years
	93 (45.1%)	42 (20.4%)	25 (12.2%)	19 (9.2%)	17 (8.3%)	10 (%)
Employ-ment Status	Employed full time	Employed part time	Self-employed	Student	Unemployed and currently looking for work	Unemployed and not currently looking for work
	129 62.6%)	16 (7.8%)	27 (13.1%)	25 (12.1%)	8 (3.9%)	1 (0.5%)
Job Category	Academics	Data science	Machine learning engineer	Top management CEO, Founder	Developer	Managers and consultants
	38 (18.4%)	45 (21.8%)	31 (15%)	26 (12.6%)	13 (6.3%)	26 (12.6%)
Years in the AI profession	0	1-2	3-4	5-6	7-8	9-10
	16 (7.8%)	72 (34.9%)	65 (31.5%)	35 (17%)	13 (6.3%)	5 (2.4%)

Employment

Most respondents (62.6%) were employed full-time, while less than 5% were unemployed. Thirteen percent were self-employed, aligning with the job title of founders and incubator initiatives provided by the network.

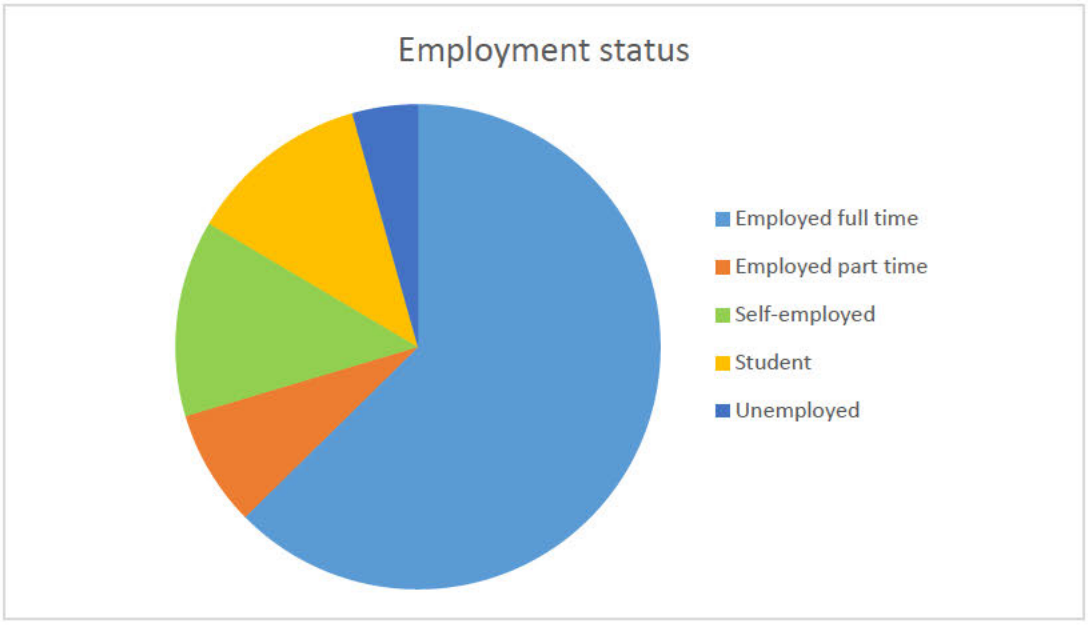

Figure 31 Employment status

Over 60% of the respondents have been working for ten or less years. This finding aligns with the age groups reported above in the demographic profile.

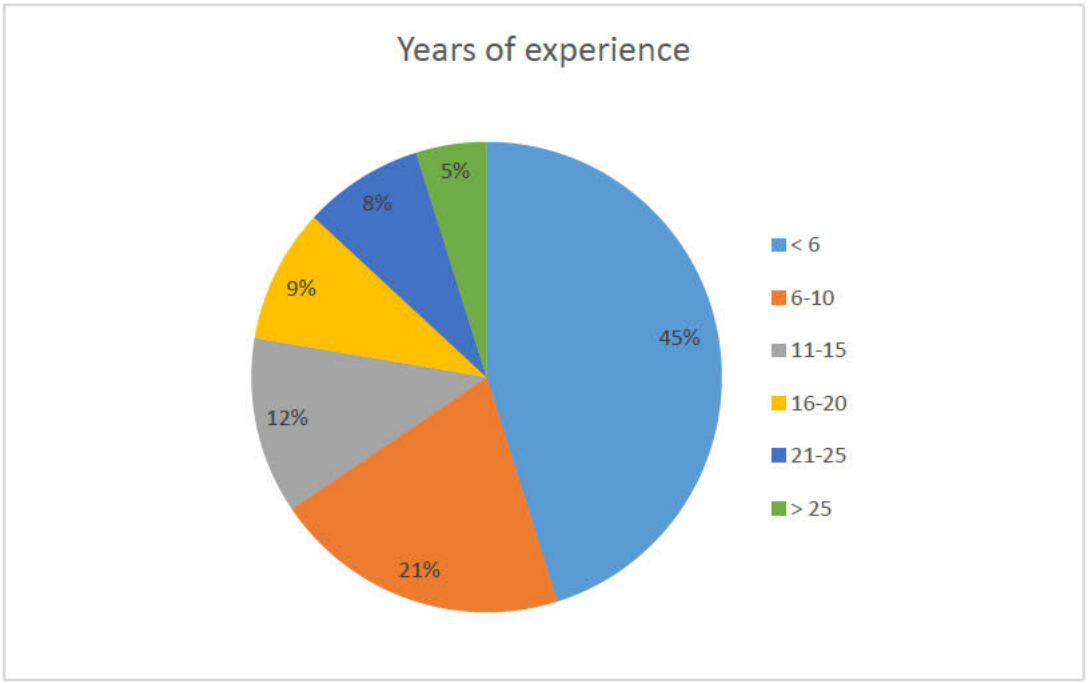

Figure 32 Working years.

Job category

The majority (36.8%) of respondents worked as data scientists or machine learning engineers at various levels, as would be expected for members of a women in an AI network. Interestingly, 11.5% of the members were CEOs, in top management, or founders or co-founders of their own businesses. Approximately 18% of respondents worked in academia in various roles ranging from PhD students to researchers to lecturers. Seven respondents classified themselves as AI ethicists (3.4%), an emerging job title.

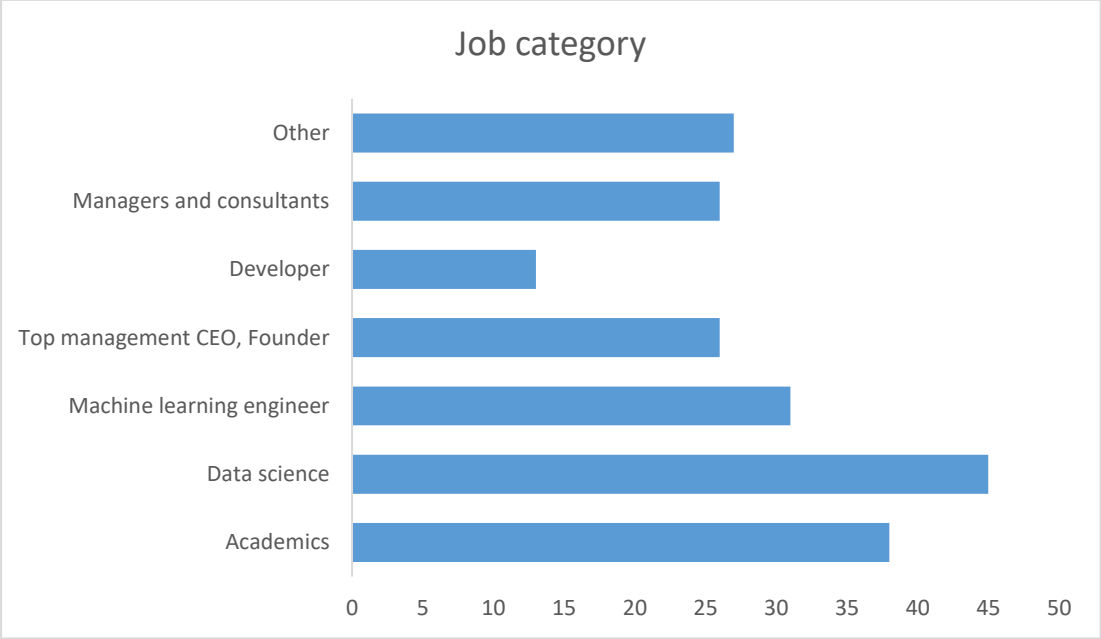

Figure 33 Job category

Years in the AI profession

The average number of years the respondents have been in the AI profession was 3.18 (SD=2.207), with the maximum number of years being 10, consistent with the newness of AI as a career. The histogram shows that the mode was only one year. The newness of the profession can explain this positive kurtosis, where the distribution had a heavier tail (Kline, 2016, p. 74).

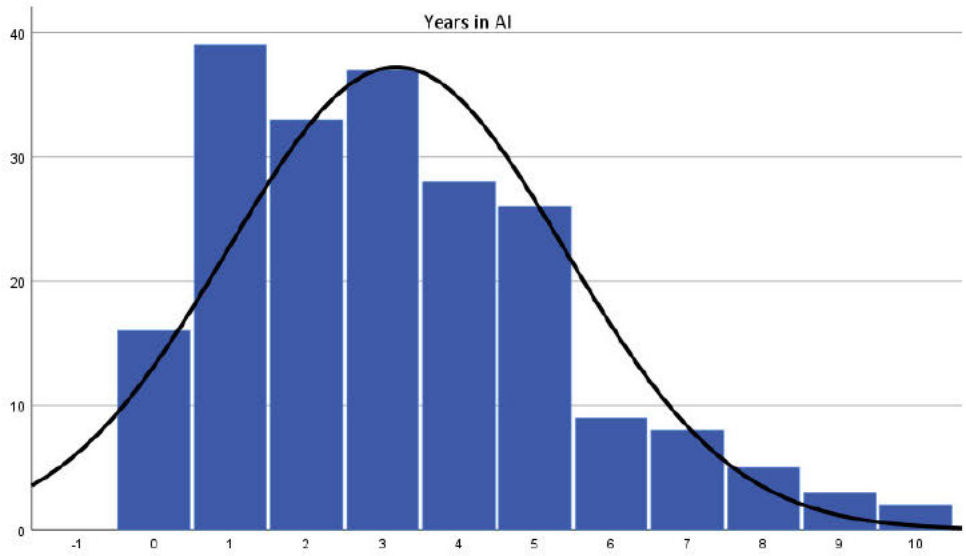

Figure 34 Years in AI profession

Having established the respondents' statistics regarding their AI careers, the next set of results provide an overview of their network activity.

4.4.3. Women in AI networks

Table 6 below shows the summary statistics related to the respondents' WAIN membership.

Table 6 Women in AI networks

N=206	**Frequencies (percentages)**					
Years in network	<1 year	1	2	3	4	>4 years
	38 (18.4%)	84 (41.3%)	38 (18.4%)	27 (13.1)	6 (2.9%)	12 (5.8%)
Reason for joining network	Job, speaking and promotional opportunities	Personal, emotional and social support	Professional advice, mentoring and education	Other		
	52 (25.2%)	22 (10.7%)	124 (60.2%)	8 (3.9%)		
Number of networks	1	2	3	4	5 or more	
	48 (23.3%)	49 (23.8%)	55 (26.7%)	24 (11.7%)	30 (14.6%)	

Years in the WAI network

On average, the number of years the respondents had belonged to the network was 1.62 (SD=1.436). Women in AI networks are a recent development, and the distribution reflects the network's fast growth, with the number of years of membership skewing to the low side. Most respondents are members of more than one network (76.7%), indicative of the importance of networking to the respondents.

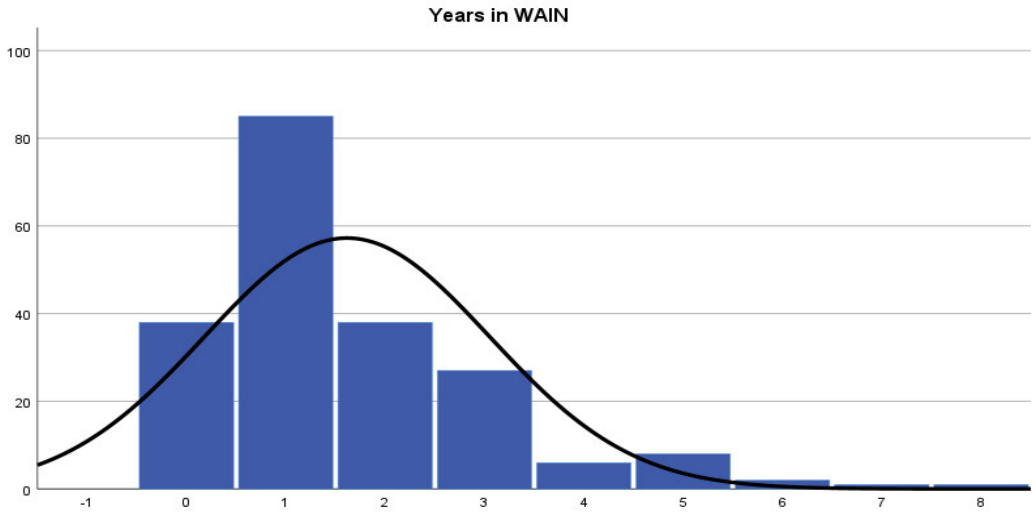

Figure 35 Years in the network

The main reason respondents selected for network membership was for professional advice, mentoring and education (60.2%). This was followed by job, speaking and promotional opportunities at 25%.

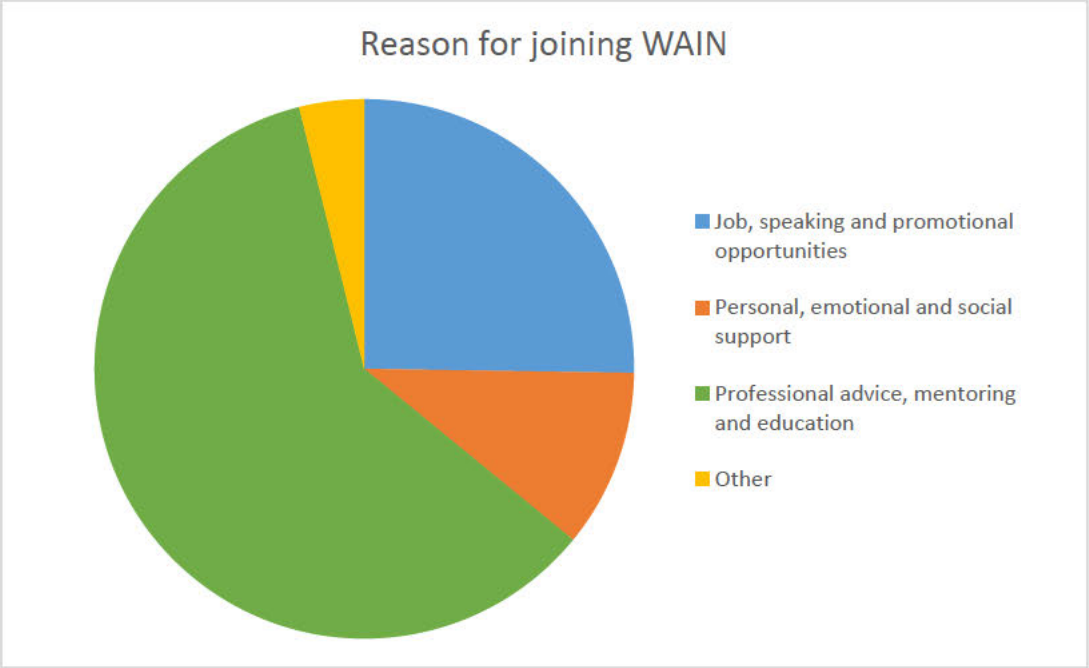

Figure 36 Reasons for joining the network.

An open-ended question was asked of participants: "What is the main benefit of the network for you?". Although a variety of answers were given, a common theme emerged – that of connection with other women in AI. For example, respondents gave answers such as "*stay connected with the people in my own profession in a non-competitive environment*" and "*mind-alike ladies who shared the same profession and passion*" and "*Getting to be a part of a community of like-minded women in tech who are passionate about using AI for good and expanding representation in the field*." These are similar to sentiments expressed by the leaders and experts on WAINs in Phase 3.

4.4.4. Structured equation modelling (SEM) results

First, in SPSS, several tests for base functions were carried out: Kaiser-Meyer-Olkin test was used to determine sampling adequacy, as recommended by Howard (2016, p. 52), with the KMO at .921 and Bartlett's test of sphericity showing that the correlations are statistically different ($P<0.5$) as required (Howard, 2016, p. 52). The data thus supported the use of factor analysis.

Table 7 KMO and Bartlett's test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.921
Bartlett's Test of Sphericity	Approx. Chi-Square	5721.287
	df	703
	Sig.	.000

The 206 cases remaining after data cleaning and screening, described in Chapter 3 met the minimum required for an EFA (Howard, 2016, p. 52). Treiblmaier and Filzmoser (2010, p. 205) recommend oblique relations methods; therefore, Promax rotation was chosen. Maximum likelihood (ML) factor extraction method was selected as a valuable method for model fit (Fabrigar, Wegener, MacCallum, & Strahan, 1999, p. 277) and is the same factoring method used by AMOS. As Howard (2016, p. 53) suggests, the ML results were compared to Principal Axis Factoring extraction method results to ensure ML assumptions were not violated. This comparison showed very similar results; therefore, the ML results were retained.

The Exploratory Factor analysis ensured that indicators were strong measures of the latent variables, with good convergent and discriminant validity, (Cheung et al., 2023, p. 2). To ensure convergent validity, all factor loadings were above .4 (Goretzko & Bühner, 2020, p. 783). Those below .5 were checked (using Cronbach's alpha) and retained for further interrogation in the CFA. All scales were measured on a 5-point Likert scale, where five indicated a high level of agreement. Internal consistency, a measure of reliability, was tested by measuring the Cronbach Alphas of the variables (Tavakol & Dennick, 2011, p. 53), summarised below:

Table 8 Scale Cronbach's alphas

Variable	Cronbach's Alpha
Career Persistence	.81
Career Advancement	.84
Networking behaviour	.88
Social Support	.89
Opportunities and resources	.88

Discriminant validity requires unidimensionality, and is needed to assign meaning to a latent variable (Cheung et al., 2023, p. 8). Items were deleted from networking behaviour, social support and opportunities variables due to cross-loading, only when not affecting the overall theoretical model. As evidence of divergent validity, there were no strong cross-loadings, with no loadings on secondary factors above .30 (Howard, 2016, p. 56). Convergent validity was evidenced with Average Variance Extracted (AVE) all above .5, while construct reliability was above .7, indicating adequate convergence or internal consistency (Cheung et al., 2023, p. 7; Hair Jr, Sarstedt, Ringle, & Gudergan, 2017, p. 56). Discriminant Validity was evidenced by the square root of the AVEs being less than the absolute value of the correlations with factors, and being less than the Maximum Shared Variance (MSV) (Treiblmaier & Filzmoser, 2010, p. 207). Standardised loading estimates were .7 or higher. MSV also provided evidence of convergent validity (Hair Jr et al., 2017; Treiblmaier & Filzmoser, 2010, p. 207).

Table 9 Reliability and validity

	CR	AVE	MSV	MaxR(H)	Career advance	Social support	Nw behav	Opport	Career persist
Career advancement	0.830	0.556	0.201	0.864	**0.746**				
Social support	0.927	0.717	0.508	0.935	0.448	**0.847**			
Networking behaviour	0.883	0.519	0.508	0.884	0.324	0.713	**0.720**		
Opportunities	0.894	0.628	0.504	0.897	0.380	0.710	0.688	**0.792**	
Career persistence	0.812	0.521	0.092	0.818	0.303	0.242	0.271	0.299	**0.722**

Communalities reflected adequacy, all being above .3 and factor loadings were above .4 (Howard, 2016, p. 55). The EFA accounted for 63% of the total variance explained. The visual spree plot aligned with the number of factors extracted, as recommended by Williams, Onsman, and Brown (2010, p. 7).

Common method bias was tested using Harman single factor test, a suitable test in business research (Fuller et al., 2016, p. 3198), and no issues of concern regarding model bias were found. A relatively short questionnaire was also used to reduce common-method variance as Podsakoff, MacKenzie, and Podsakoff (2012, p.563) recommend. Regarding normality and outliers, Kurtosis and critical ratios were within range, meaning data was normally distributed. Multicollinearity was tested in SPSS, all VIFs were less than 3.3, indicating no issues of concern (Kline, 2016, p. 427). A listing of cases farthest away from the centroid (Mahalanobis distance) (Kline, 2016, p. 73) resulted in no cases needing removal.

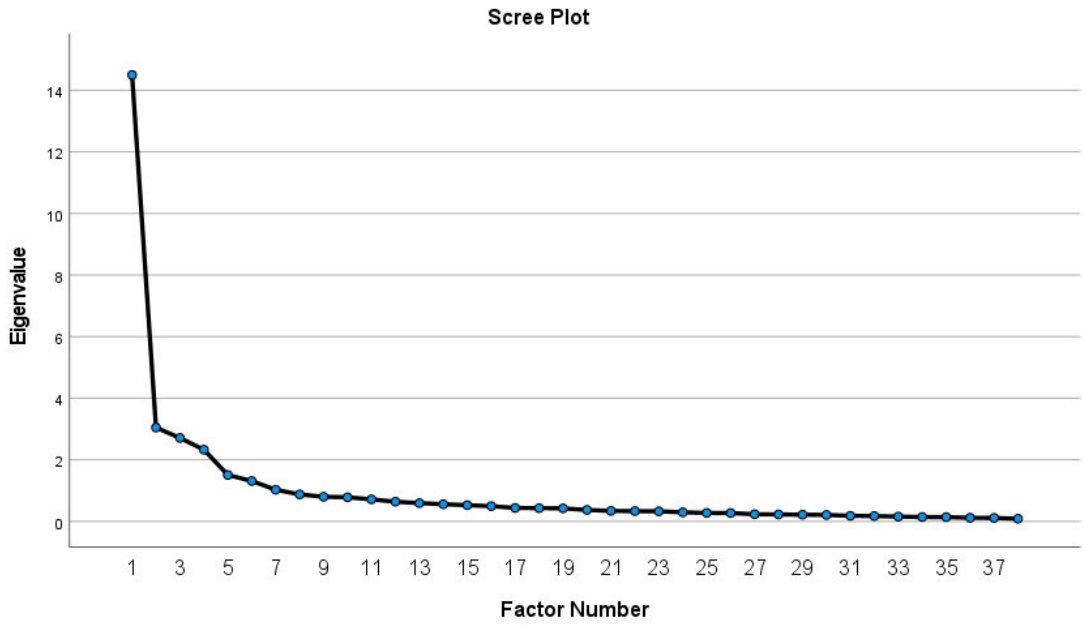

Figure 37 Scree plot

The pattern matrix supported the theoretical model, with factors loading above .4. (Howard, 2016, p. 60). The results of the pattern matrix in the EFA were used to create the initial CFA model in AMOS. The CFA validated the EFA factor analysis. The purpose of the CFA was to analyse how well the indicators measured the latent variables (Brown, 2015, p. 42) – networking, career persistence, career advancement, social support and opportunities and resources. The CFA also accounted for unobservable covariance, while standardised factor loadings allowed estimation of the direct effect (Jackson, Gillaspy Jr, & Purc-Stephenson, 2009, p. 19). From the initial CFA, one indicator each from Career advancement and Career persistence was removed due to low factor loadings, the remaining four items each still adequately measured the constructs without jeopardising the theoretical model (Brown, 2015, p. 53). Some error terms of indicators in the same variable were covaried, where logical, due to the indicators being based on similar questions (Brown, 2015, p. 37). After that, the standardised residual covariances were assessed to determine significant variance (over 2) influencing the overall model fit, resulting in the deletion of items from the latent variables of networking behaviour, social support and opportunities while maintaining a minimum of four indicators per variable (Kyriazos, 2018, p. 2214). The results of the CFA are shown in Figure 38 below.

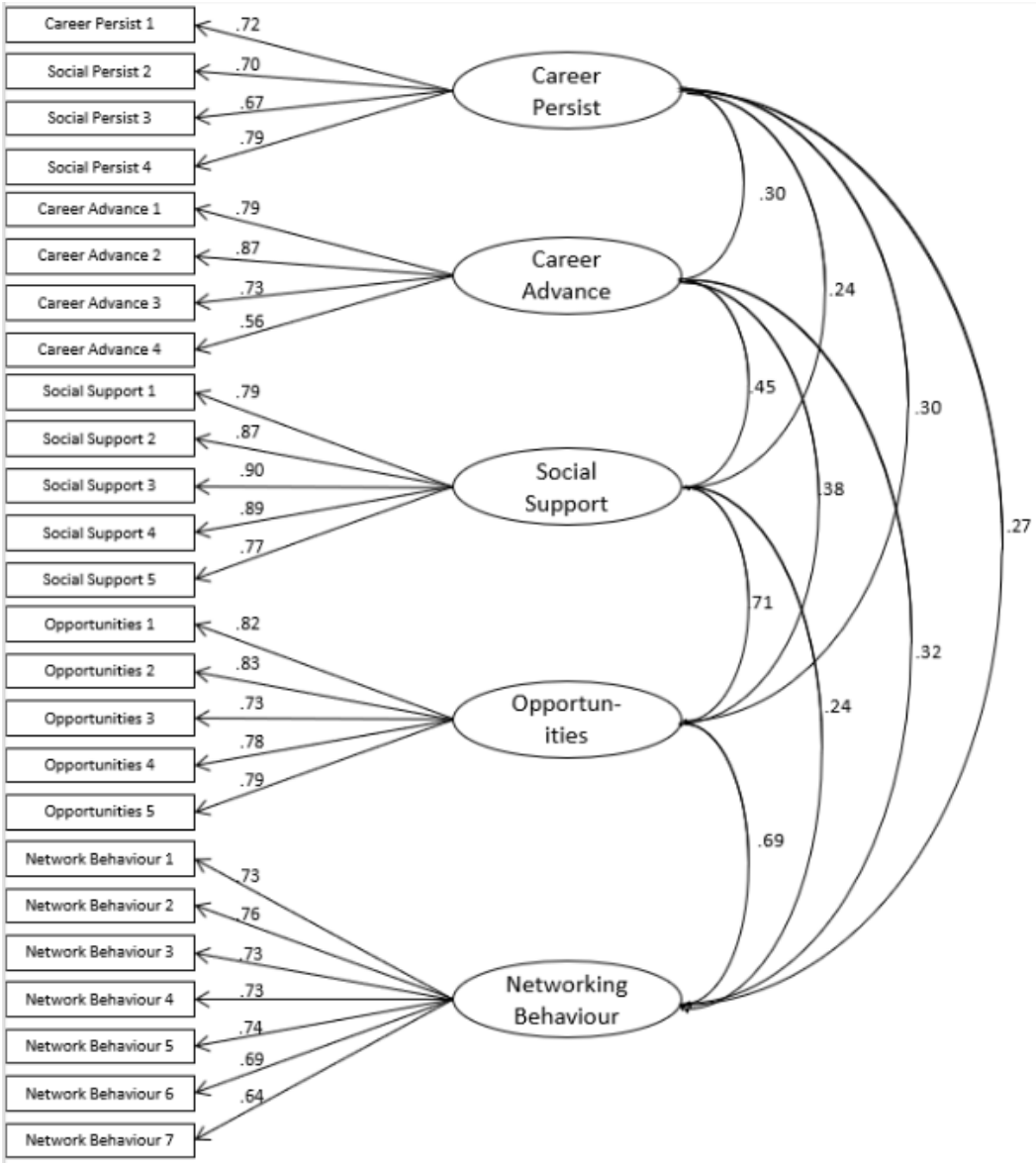

Figure 38 CFA

A path diagram from the CFA was then created, where the hypotheses from the Phase 2 results were tested through the path model generated in AMOS, shown in Figure 39 below. All relationships remained the same as the model from the Phase 2 findings, except for an additional relationship between social support and opportunities and resources, which improved model fit. The relationship makes theoretical sense since socially supported members are more likely to take advantage of the opportunities and resources offered by the network (Porter et al., 2023, p. 37). The path model with hypothesised relationships is shown in the figure below.

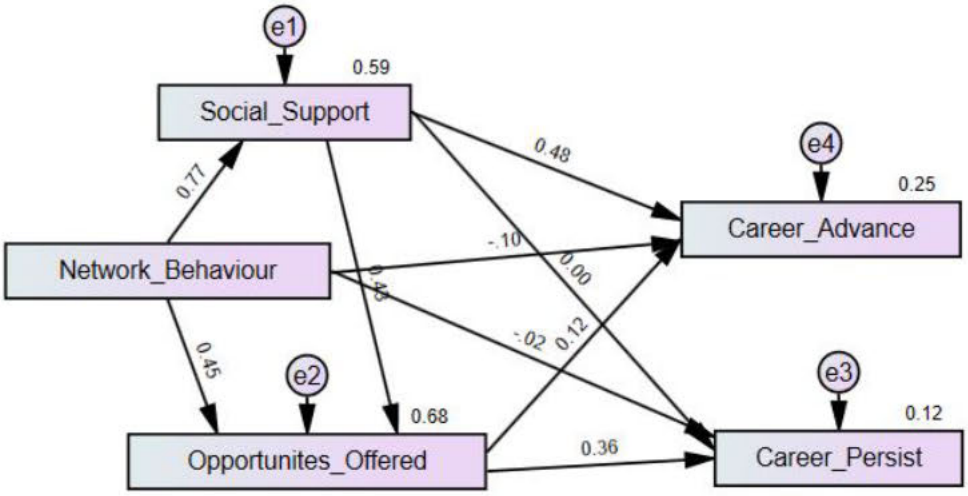

Figure 39 Initial path model

The results are shown in the table below:

Table 10 SEM results

SEM Results	Estimate	S.E.	CR	Sig
Social Support <- Networking Behaviour	1.005	.59	17.150	***
Opportunities <- Networking Behaviour	.559	.077	7.297	***
Opportunities <- Social Support	.414	.059	7.065	***
Career Advancement <- Social Support	.365	.080	4.581	***
Career Persistence <- Opportunities	.239	.077	3.118	.002
Career Advancement <- Networking Behaviour	-.103	.105	-.982	.326
Career Persistence <- Networking Behaviour	-.0.14	.094	-.144	.886
Career Persistence <- Social Support	.002	.072	.025	.980
Career Advancement <- Opportunities	.094	.085	1.100	.271

*** statistically significant

Hypotheses can be accepted if the critical ratio and p values are insignificant (t >1.96 and the p <0.05) (Jackson et al., 2009). Direct relationships were hypothesised after tests for statistical power (0.99). The results show no direct relationship between networking behaviours and career persistence and advancement, detailed in Table 11 below.

Table 11 Direct relationships hypotheses

Hypotheses	Standardised estimates	CR	p-value	Result
Networking behaviour ->Career advancement (direct)	-.104	-.982	.326	Null hypotheses accepted
Networking behaviour ->Career persistence (direct)	-0.16	-.144	.886	Null hypotheses accepted

Bootstrapping was used to test the indirect effects of networking behaviour on career persistence and advancement through the mediators of social support and opportunities and resources. Bootstrapping is a resampling method that simulates random sampling to create confidence intervals in mediation analysis (Kline, 2016, p. 68). This method multiplies the regression coefficients of various paths; for example, in Figure 40 below, Path A x B provided the mediation results for the indirect effect of networking behaviour on career persistence. Social support and opportunity and resources are the two mediating factors. The indirect, direct and total effects were included in the analysis in AMOS. After bootstrapping (2000 bootstrap samples, 95% BC confidence level) the following mediated relationships were observed.

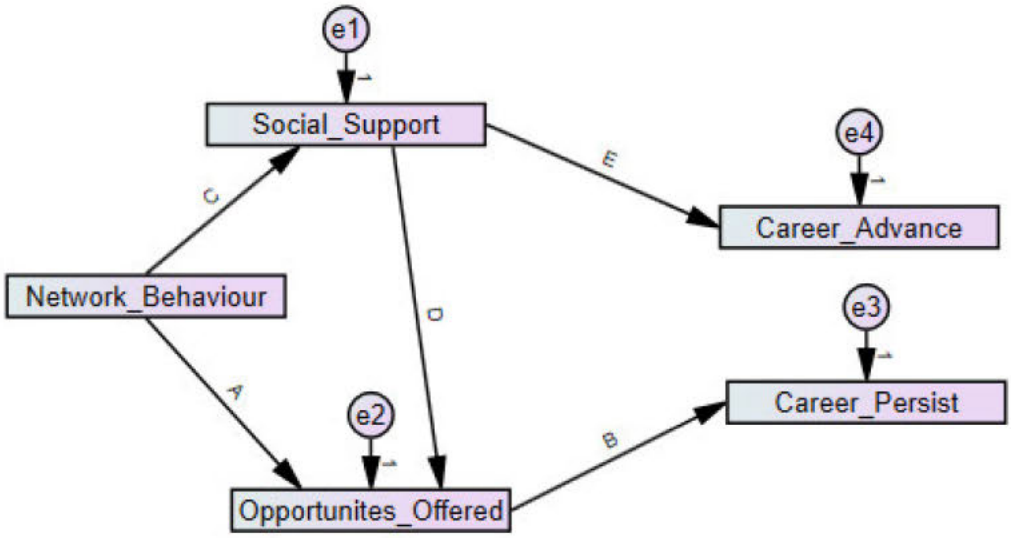

Figure 40 Path model for mediation

The results of the analysis are shown in the table below:

Table 12 Indirect relationships hypothesised (mediated)

Hypotheses	B/S est.	Lower bound	Upper bound	p-val	Results
Networking behaviour -> Opportunities -> Career advancement	0.52	-0.48	.218	.345	Null hypotheses accepted
Networking behaviour -> Opportunities -> Career persistence	0.133	.031	.279	.007	Null hypotheses rejected
Networking behaviour -> Social support -> Career persistence	.002	-.189	.201	.999	Null hypotheses accepted
Networking behaviour -> Social support -> Career advancement	0.99	.033	.185	.006	Null hypotheses rejected

The direct effects between networking behaviour and career advancement (.335) and career persistence (.937) were insignificant and dropped from the model. The indirect effects between the mediating variables of social support and opportunities were tested and found to be significant. However, there was no significant effect between social support and career persistence (.965) and opportunities and career advancement (.580). Controlling for age or years in AI had no significant effects on any of the endogenous variables. Thus, full mediation through social support was found between the impact of networking behaviour on career advancement with a significant positive indirect effect (b = .99, p = .006). In addition, full mediation through opportunities and resources was found between the impact of networking behaviour on career persistence with a significant positive indirect effect (b = .133, p = .007). Finally, serial mediation through social support to opportunities and resources was found to be significant (b = .096, p = .00). The total indirect effect (b = .0226) of networking behaviour on career persistence was significant (CI = .133, 323, p = .001). The significant relationships are summarised in Table 13 below:

Table 13 Significant relationships - mediation results (bias-corrected 95%)

Significant relationships	B/S est.	Lower bound	Upper bound	p-val	Results
Networking behaviour -> Opportunities & resources -> Career persistence	0.133	.031	.279	.007	Full mediation
Networking behaviour -> Social support -> Career advancement	0.99	.033	.185	.006	Full mediation
Networking behaviour -> Social support -> Opportunities & resources -> Career persistence	.096	.058	.159	.000	Full Serial mediation

The final model, with significant relationships shown in Figure 41 below.

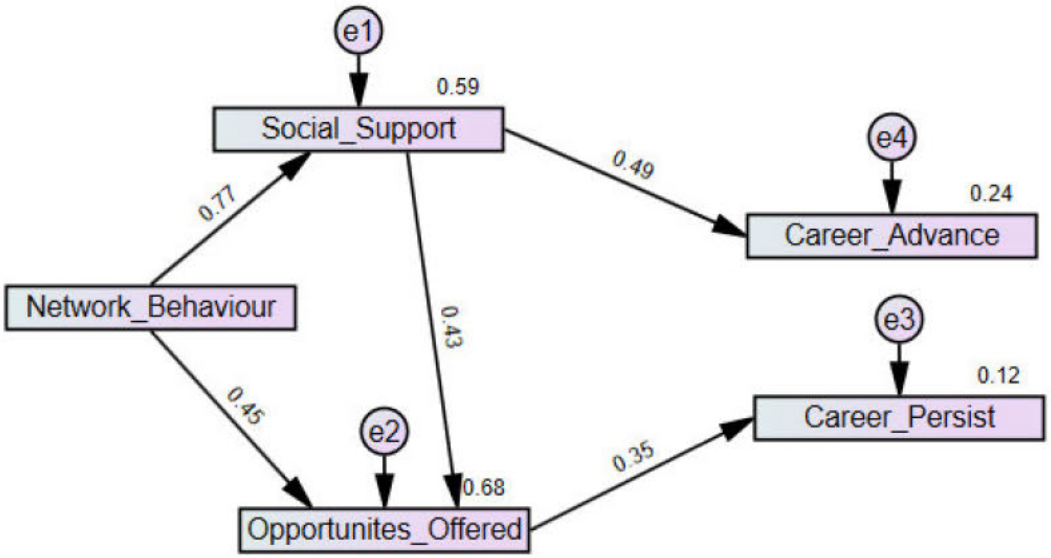

Figure 41 Final model

The final model fit indices are shown in the table below, with the threshold levels and interpretations according to Hooper and Coughlan (2008, p. 58).

Table 14 Model fit indices

Model fit index	Absolute fit indices					Incremental fit indices		
	X/DF	RMSEA	SRMR	GFI	AGFI	CFI	NFI	TLI
Threshold levels	<=5	<0.07	<0.08	>0.95	>0.95	>0.95	>0.95	>0.95
Score achieved	1.493	0.46	0.039	0.986	0.959	0.996	0.986	0.993
Interpret-ation	Good fit, adjusts for sample size.	Good fit, has a known distribution and favours parsimony.	Good fit, standardised average squared differences between estimates.	Good fit. Should be used in conjunction with AGFI.	Good fit. Adjusts the GFI based on number of parameters in the model.	Good fit	Good fit. Assesses fit relative to a baseline model.	Favours parsimony.

Overall, the model fit indices show a high degree of model fit, allowing for the summarised results in Table 15, showing the significant findings from the final model (Significance p<.001).

Table 15 Supported hypotheses

Hypothesis	Indirect effect	Results
Networking –> opportunities offered > career persistence	.274	Full mediation
Networking –> social support -> career advancement	.379	Full mediation

4.4.5. Descriptive analysis of variables

Regarding career persistence, respondents reported a positive commitment to the AI profession (M=3.8, SD=1.219), indicating the likelihood of persisting in the AI profession. The item with the lowest variance and highest mean was “I would be very happy to spend the rest of my career in this profession” (M=4,25, SD=0.944), indicating respondents' high attachment to the AI profession. Respondents reported satisfaction with their progress in the AI profession (M=3.67, SD=0.959), reflective of their success in advancing in the AI profession. The highest scoring item related to skills development (M=3.87, SD=0.907), which is one area networks provide support in.

Table 16 Career persistence and advancement variables with indicators

Career Persistence (α =.809) (M=3.8, SD = 1.06)	Mean	SD
I would be very happy to spend the rest of my career in this profession	4.25	.944
I feel a strong sense of belonging to my profession	3.83	1.043
I feel emotionally attached to this profession	3.70	1.044
I don't think that I could easily become as attached to another profession as I am to this one	3.44	1.219
Career Advancement (α = .843) (M=3.7, SD = 0.96)	**Mean**	**SD**
I am satisfied with the progress I have made towards meeting my goals for the development of new skills	3.87	.907
I am satisfied with the progress I have made towards meeting my overall career goals	3.63	.993
I am satisfied with the progress I have made towards meeting my goals for advancement	3.61	.929
I am satisfied with the success I have achieved in my career	3.55	1.010

Women in AI's networking behaviour was neutral (M=3.48 SD=1.207), with the indicators ranked from highest to lowest in the table below. "I take on roles and tasks in the network which could also be useful to me professionally" was the highest scoring item (M=3.88 SD=1.04). The scale provided reliable, indicated by a Cronbach's alpha of .882.

Table 17 Networking behaviour variable with indicators

Networking behaviour (α = .882) (M=3.48 SD=1.207),	Mean	SD
I take on roles and tasks in the network which could also be useful to me professionally	3.88	1.034
I accept invitations to network events	3.86	1.027
I use my contacts in the network to ask for advice	3.61	1.236
I am an active member the network	3.35	1.255
I meet network members that could be of professional importance to me at casual get-togethers	3.31	1.265
When I cannot solve a problem at work I consult network members and ask for advice	3.23	1.344
I use network events to talk to network acquaintances on a personal level	3.11	1.291

Social support offered by the network was measured by items in the table below and found to be neutral (M=3.41, SD=1.242), with the Cronbach's alpha of .894 reflecting a highly reliable scale.

Table 18 Social Support variables with indicators

Social Support (α = 0.894) (M=3.41, SD=1.242),	Mean	SD
The network provides me with a safe space	3.76	1.142
There are people in the network I could turn to for advice if I were having problems	3.52	1.248
There are people in the network I can count on	3.42	1.222
There are people in the network who will advocate for me	3.37	1.234
I have relationships in the network that provide me with a sense of emotional security and well-being	3.33	1.265

Opportunities provided by the network, such as learning and job opportunities, scored neutrally (M=3.47, SD=1.14). The item scoring highest related to expanding professional knowledge (M=3.92, SD=1.011), which aligns with the item the WAIN members found most satisfactory about their career progress. The scale is reliable, as measured by a .883 Cronbach alpha.

Table 19 Opportunities and resources variable with indicators

Opportunities & resources (α = .882) (M=3.47, SD=1.14)	Mean	SD
My network provides opportunity to expand my professional knowledge	3.92	1.011
My network develops my work-related abilities	3.67	1.058
My network helps ensure that my work-related abilities and knowledge are up-to-date	3.55	1.133
My network supports me in my career development	3.36	1.129
I constantly stay up-to-date about employment opportunities in the labour market through my network	3.31	1.242

Having provided an overview of the descriptive statistics for the scales, the next set of results pertain to the development of the structured equation model, beginning with exploratory and confirmatory factor analyses.

4.4.6. Discussion of Phase 3 results

For this phase, there were two objectives related to testing the model from Phase 3.

The first objective for Phase 3 was "*To determine WAIN members' women's career persistence and advancement in the AI profession*". Career persistence was relatively high (M=3.8, SD=1.219), with most members attached to the AI profession to the extent they would be happy to remain in the profession for the remainder of their career (M=4,25, SD=0.944). With persistence being an essential factor in women staying in AI and necessary for more inclusive AI development teams, this is an important finding

for women to advance in the profession. As indicated by the expert panel in Phase 2, WAIN members are highly attached to the AI profession. This finding is in contrast to recent research, which found that even in equal societies such as Sweden, career resilience in IT is lower for women due to lack of support and that overall, women in AI face significant barriers preventing them from persisting in the field (Roopaei et al., 2021, p. 499; Tokbaeva & Achtenhagen, 2023, p. 254). Literature shows persistence for women in IT has been an enduring and systematic problem (e.g. Armstrong et al., 2018, p. 1; Avila et al., 2018, p. 2; Gallivan, 2013, p. 45; Gorbacheva et al., 2019, p. 43). The current research finds WAINs are particularly important in supporting women to persist in the field.

Regarding advancement in AI, WAIN members were generally satisfied with their progress (M=3.67, SD=0.959). Again, this is in contrast to other research, as women in AI and IT in general experience barriers to advancement (Armstrong et al., 2018, p. 2; Gorbacheva et al., 2019, p. 51; Roopaei et al., 2021, p. 497), suggesting WAIN membership supports progression in the AI field, an important finding given the importance of finding ways to support women in AI (Schulenberg et al., 2023, p. 183).

The second objective was "*To determine the relationships between networking behaviour and WAIN member career persistence and advancement in AI*." The study sought to assess the impact of WAIN member networking behaviour on members' career persistence and advancement. Although no direct effects were evidenced, for career advancement, the squared multiple correlation was 0.24, indicating that 24% variance in career advancement is accounted for by networking behaviour through the social support the network offered. For career persistence, 12% of the variance is accounted for by networking behaviour through the opportunities and resources the network offered. With no direct relationship between networking and career persistence and advancement, a fully mediated effect between networking via social support for career advancement was found, and similarly, from networking to career persistence via resources and opportunities offered. Serial mediation from networking to social support to opportunities and resources to career persistence was also evidenced.

The results suggests that while networking behaviour itself does not directly impact career advancement and persistence, it plays an important role through indirect

effects. For career advancement, the effect is through social support, while for career persistence, the effect is through opportunities and resources and social support. This finding highlights the importance of social support and the availability of opportunities and resources within a professional network in supporting women in AI.

Table 20 Results of hypothesis testing

Hypothesis tested	Result
H_1 = The more networking behaviour displayed by women in AI, the more they will persist in their careers in AI (direct relationship).	Rejected
H_2 = The more networking behaviour displayed by women in AI, the more they will advance their careers in AI (direct relationship).	Rejected
H_3 = The positive impact of networking behaviour on women in AI career persistence is mediated by the social support offered by the network.	Accepted
H_4 = The positive impact of networking behaviour on women in AI career advancement is mediated by the social support offered by the network.	Partially Accepted
H_5 = The positive impact of networking behaviour on women in AI career persistence is mediated by the opportunities and resources offered by the network.	Accepted
H_6 = The positive impact of networking behaviour on women in AI career advancement is mediated by the opportunities and resources offered by the network.	Rejected

The relationship between social support and career advancement was also evidenced in a systematic review by Greer and Kirk (2022, p. 8), who found that social support improves advancement in specific careers, especially in allowing network members to gain knowledge. Jacobs, De Vos, Stuer, and Van der Heijden (2019, p. p5) contend that networking behaviour provides social connections and resources that offer career advantages and also found little evidence of a direct relationship between networking and careers. Further, network members proactively seek relatedness, which in turn

provides resources beneficial to members' careers (Jacobs et al., 2019), similar to the serial mediation found in the results of this study. Wanigasekara et al. (2022, p. 27) found continuous career commitment is enhanced through networking resources, similar to this phase's results.

This study found direct relationships between women in AI networking behaviours and their career advancement and persistence were non-significant. This finding is similar to findings by Wanigasekara et al. (2022, p. 27), who surmised that differences may be attributed to the types of careers. No other similar research has specifically focused on women in the AI profession, despite diversity in AI development teams being an acknowledged imperative (Roopaei et al., 2021). Interestingly, Wanigasekara et al. (2022, p. 28) found that external networking behaviour is higher for more highly educated professions, which aligns with the high percentage of post-graduate WAIN members in this research.

4.5. Conclusion

This chapter reported the results of each phase, including interpretation and discussion of the findings, following the objectives per phase outlined in Chapter 3. The first phase highlighted the need for a socio-technical examination of gender bias, supporting the premise for the initial model, which was then explored in Phase 2. The qualitative review of international experts provided further refinement for the model, which was then tested in Phase 3. This final quantitative study tested and provided a final adaptation of the model. The results showed the importance of network support, resources and opportunities in the relationship between WAIN member networking behaviour and their AI career persistence and advancement. This three phased approach met the overall research objective of exploring how WAINs support women in advancing and persisting in the AI field. The next chapter synthesises the findings and provides an overall discussion of the research, examining the details and relationships between the results from a holistic perspective related to the overall research questions. Additionally, the limitations and contributions of the study are presented.

Chapter 5. CONCLUSIONS AND CONTRIBUTIONS

5.1. Introduction

This final chapter aims to synthesise discussion from all three phases according to the overall objectives of the study. Whereas previous chapters provided the findings per phase, this concluding chapter integrates the findings, contributions and recommendations to provide a holistic summary of the study. Important aspects from the discussion and findings of the research are provided, organised according to the six overall research objectives that cross phases. The results are presented in relation to the research objectives and questions, from which conclusions are drawn. Theoretical and practical contributions are provided, to show the research's original and substantial contributions. This section is followed by recommendations organised by stakeholders who could use the research. The associated limitations and recommendations for future research are also described. Finally, conclusions that encompass all the research contributions conclude the chapter and thesis.

5.2. Synthesis Discussion of Research Objectives and Questions

This research aimed to determine if women in AI networks support women in AI careers, with the premise that more women in AI mitigates gender bias in AI solutions. A synthesised discussion of the findings across phases, according to the overall research objectives and questions, as outlined in Chapter 1, follows.

5.2.1. Research Objective 1

> *To systematically review the current state of research into the social causes and consequences of, and solutions to, gender bias in AI.*

There were three components to this objective: the causes of AI gender bias, the consequences of gender bias in AI, and potential solutions to reducing gender bias in AI algorithms. These objectives were met at the conclusion of Phase 1. A paper describing the findings was published in the journal ‘Online Information Review’ (Hall & Ellis, 2023). Through a comprehensive systematic review, the analysis was

presented with a socio-technical lens. This approach, where the review focused on social factors rather than “techno-solutionism” prevalent in AI research, has been subsequently supported and validated as a worthwhile focus, requiring a multi-disciplinary approach (Schwartz et al., 2022, p. 11). The review found that the majority of previous research focused on technical aspects alone, a limited approach that has faced criticism (Whittaker et al., 2018, p. 11). Rather, the human or social side should be the focus (Singh et al., 2020, p. 1285) and is justified given how many sectors and actors are affected (Raisch & Krakowski, 2021, p. 33).

RQ1a: What are the social causes of AI gender bias?

The social causes of AI gender bias were equally attributed to the design of the AI algorithms and the data sets used to train AI models. Of relevance to the other phases of this research, 43% of the design causes were attributed to lack of gender diversity in AI development teams. This finding supports the premise for this research, highlighting the importance of increasing women's participation in AI development teams as a practical and ethical priority. More recent research supports this finding, with underrepresentation of women in AI design and development creating ‘blind spots’, limited by the designers’ experiences (Nadeem et al., 2022, p. 8; Schulenberg et al., 2023, p. 177).

RQ1b: What are the consequences of AI gender bias?

Consequences of AI gender bias were far-reaching and varied in the systematic review, with the amplification of gender bias being the most common consequence cited in the papers reviewed. This finding signifies the importance of finding ways to improve gender diversity in AI, supporting the need for this research. Amplification occurs through the feedback loop mechanism, where gender-biased outcomes are reintroduced, further reinforcing these biases (Ferrara, 2023, p. 2; Wellner, 2020, p. 129). Amplification of gender bias is also the most serious and far-reaching of the consequences for society and business, as reported and confirmed by recent research (Bohdal et al., 2023, p. 2; Nadeem et al., 2022, p. 8; Shrestha & Das, 2022, p. 13). O’Connor and Liu (2023, p. 10) suggest “it is not a question of either/or as to whether to first change society or change AI, both must be achieved in tandem”.

RQ1c: What social solutions are there to gender bias in AI?

Results showed that improving gender diversity in AI development teams was the most common solution in the category relating to the design of AI algorithms. This finding makes sense, given this was also the most common cause of the bias. Of note for the other phases of this research, is that research called for more support for women in the AI profession to increase representation in AI development teams, primarily through organisations such as Women in AI networks (Cerit et al., 2020, p. 1; Roopaei et al., 2021, p. 500).

The results of the systematic review in Phase 1 thus met the research objective to determine the current state of research into gender bias in AI algorithms. Further, the results provided impetus and justification for the next research phase, where networking is proposed to improve gender representation in the AI workforce by supporting women in persisting and advancing in AI careers.

5.2.2. Research Objective 2

> *To develop a model of women in AI networking and career persistence and advancement*.

This objective was met in Phases 2 and 3 of the research, which answered the call for further study into women-only networks, ideas to improve diversity and inclusion in AI development teams and focus on non-technical factors in AI bias (Annabi & Tari, 2018; Gorbacheva et al., 2019; West et al., 2019). The imperative to increase gender diversity in AI development teams was established in the systematic review from Phase 1, which proposed actionable solutions that enhance the advancement of women in AI to more prominent positions in AI development teams while supporting their persistence in such careers. The initial model drew on theory related to IT careers, women in IT, and networking behaviour, which was then explored and refined with women in AI experts in Phase 2 of the research and tested in Phase 3.

RQ2: How do WAINs impact on career persistence and advancement?

The framework and research propositions arising from the initial theoretical model were explored in Phase 2, qualitatively with WAIN experts and leaders. Expert opinion

solidified the primary constructs and relationships in the model while introducing a more nuanced understanding of the central concepts and adding new perspectives on the importance of social support. Based on the expert interview data analysis, confirmation of the networking and career constructs and the direct relationship between them from the initial conceptual model was achieved. Gender identity was removed, having been disputed as a moderating factor by the women in AI experts, while AI professional identity was absorbed into career persistence. The mediating construct of learning opportunities expanded to include more types of resources and opportunities. A more general and inclusive construct of opportunities and resources offered by WAINs resulted. A new mediating construct – social support - was introduced based on recommendations from the WAIN experts and verified in later analysis. The importance of mentorship and role models was emphasised but noted as being part of both opportunities and social support offered by WAINs and was therefore subsumed into mediating variables of social support and opportunities and resources. The resulting refined model from phase is reproduced below:

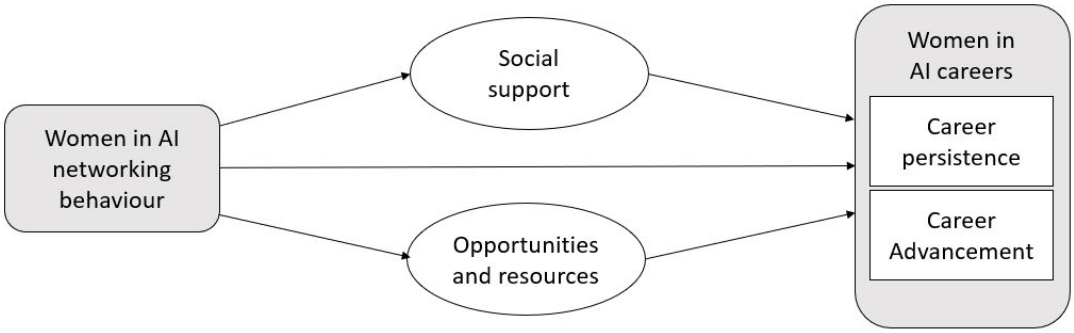

Figure 42 Model after Phase 2

Phase 3 successfully interrogated and refined the model developed in Phase 2 and achieved Objective 2. Through structured equation modelling, the direct relationship between networking behaviour was removed, while an additional serial mediation between social support and opportunities and resources was included, as depicted in the figure below:

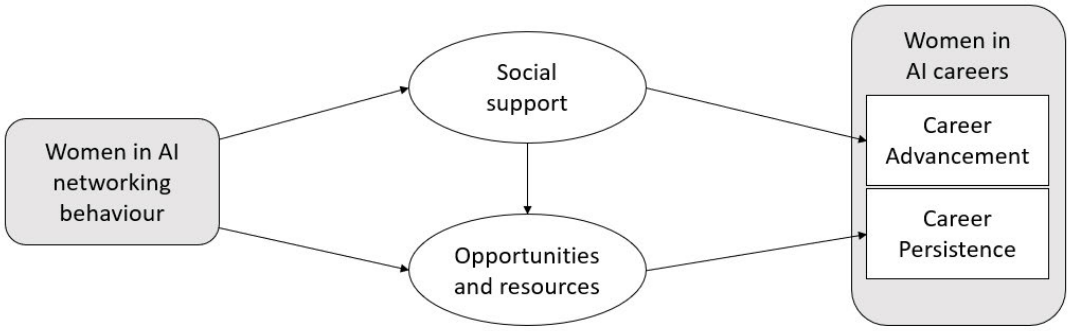

Figure 43 Model after Phase 3

5.2.3. Research Objective 3

To investigate women in AI career persistence and advancement

The model completed per the previous objective depicted WAIN member career persistence and advancement in the AI field as a dependent variable. The entire premise of the research rests on understanding how this career persistence and advancement can be supported, given the importance of increasing gender diversity in the AI workforce. The results of Phase 1 and previous research (e.g.Roopaei et al., 2021, p. 498; Schulenberg et al., 2023, p. 177) provide a rationale for this premise. Research Objective 3 was met by answering the following associated research questions:

RQ3a: How are WAIN members persisting in the AI profession?

From Phase 2, it became evident that career persistence cannot be taken for granted, given the experiences of women in AI, as exposed by the participants. Challenges included, for example, discrimination and lack of opportunity and support in the workplace. Roopaei et al. (2021, p. 498) explain that there is a widespread gender gap in AI due to socio-cultural discrimination. The expert panel cited a hostile work environment and lack of support as the main reasons for WAIN members not persisting in their AI careers. Literature supports this expert panel view in the broader field of information technology (Gorbacheva et al., 2019, p. 44) and in AI (Cernadas & Calvo-Iglesias, 2020, p. 173; Roopaei et al., 2021, p. 498; Schulenberg et al., 2023, p. 179; Tassabehji et al., 2020, p. 20). Career persistence, in the opinion of the experts interviewed, is closely related to AI being part of the WAIN members' professional

identity and how attached the members are to their careers in AI. Previous research on women in IT supports this view (Smith, Smith, & Varey, 2015, p. 108).

Phase 3 supported much of what the women in AI experts suspected – that WAIN members have a positive commitment to stay in the profession, which includes an emotional attachment related to professional identity. This commitment underscores the impact of the WAIN on its members' persistence in AI profession, with a strong sense of belonging. Women in AI and the broader IT industry, typically encounter obstacles that lead to lower career persistence, thus suggesting that networking could be the support women need to stay in the profession. Tokbaeva and Achtenhagen (2023, p. 254) explain that women in AI often experience a sense of isolation throughout the career development, showing the importance of WAINs in encouraging women to persist in the field.

RQ3b: How are WAIN members advancing in the AI profession?

The WAI experts in Phase 2 exposed the lack of resources, support and opportunities in the workplace as hindering the advancement of women in AI. Thus, even if women persist in their AI careers, advancing into leadership positions and equitable pay is not always realised, which aligns with previous research findings (Samuel, 2018, p. 6; Tokbaeva & Achtenhagen, 2023, p. 226; UNESCO, 2020, p. 25). Career advancement is related to satisfaction with meeting goals related to career development, success, income and skill development, also supported by Spurk, Hirschi, and Dries (2019, p. 51). Phase 3 results showed that WAIN members are satisfied with their progress along these dimensions, especially related to attaining career development and skills, although less so with income goals. With gender-based salary differentials still reported (Roopaei et al., 2021, p. 500), this finding is not unexpected. As the women in AI experts agreed, the resources provided by WAINs, and opportunities that members enjoy, assist women in gaining skills and eminence necessary to advance in the AI field.

5.2.4. Research Objective 4

To examine women in AI networking behaviour.

The networking behaviour of WAIN members was explored in Phase 2 of the study from the perspective of WAIN experts and leaders, and in Phase 3 from the members' perspective.

RQ4: *What networking behaviour do members of WAINs display?*

Phase 2 sought to understand WAIN member networking behaviour by examining expert opinions of network building, leveraging and maintaining behaviour in WAINs. Ultimately, many of the behavioural characteristics from the construct overlapped; for example, attending networking events demonstrated both network building and maintenance behaviour. Phase 3 results provided empirical support for positive networking behaviour exhibited by members. The women in AI expert panel emphasised the importance of volunteering and being active members, not only for altruistic reasons but because of the exposure, learning, and networking opportunities this provides. The expert panel deduced that the more effort put in and the more active and consistent members were in their networking behaviour, the more they would get out of their membership.

Phase 3 results showed that WAIN members are active in networking. The importance of active networking for women has been shown in previous research (e.g. Bapna & Funk, 2021, p. 593; Woehler et al., 2021, p. 209). The experts noted the shift in networking behaviour to more virtual networking brought about by the COVID-19 pandemic, similar to research by Tasselli and Sancino (2023, p. 153). Asking for advice from other members, whether a personal connection had already been made or not, is key networking behaviour identified by the expert panel in Phase 2, and evidenced in Phase 3 results. Overall, both Phase 2 and 3 results provide insight into networking behaviour displayed by WAIN members. The benefits provided through networking behaviour are examined in the next objective.

5.2.5. Research Objective 5

To explore Women in AI Network (WAIN) benefits and resources

Phase 2 results show that resources and benefits in the form of opportunities offered by WAINs are extensive and varied, confirming constructs from the initial conceptual model. The construct of learning resources ranged from workshops to events to skills development. The WAIN experts in Phase 2 expanded this construct, suggesting career opportunity resources such as job boards, sponsorship, start-up support, and even volunteering. According to Woodwark, Wood, and Schnarr (2021, p. 436), programs explicitly designed to support start-up initiatives illustrate the importance of networking. The importance of networking for job opportunities was also established in research by Wanberg et al. (2020, p. 578).

The various resources and opportunities offered by WAINs were consolidated into a single construct in Phase 2, called opportunities and resources. This construct includes opportunities to improve AI knowledge and skills, such as events, workshops, mentors, bootcamps, and master classes. These resources and opportunities are geared toward supporting women in developing and supporting their careers and work-related abilities. Further, the resources and opportunities allow women to stay up to date with the latest knowledge, development and jobs in the AI field. Research by Obukhova and Kleinbaum (2022, p. 30) also exposed opportunities arising from networking for women. Overall, the WAIN experts in Phase 2 provided detailed and nuanced insights into WAIN offerings, benefits and member usage. The range of benefits found is supported by literature, albeit not specifically for AI or even IT networks (Greguletz, Diehl, & Kreutzer, 2019, p. 2; Papafilippou, 2020, p. 5; Villeseche & Josserand, 2017, p. 6). For example Greguletz et al. (2019, p. 2) suggest networks provide access to “advice, technical knowledge, strategic insight or emotional support”, while Porter et al. (2023, p. 13) highlight the importance of instrumental support provided by professional networks. Phase 3 results verified much of the sentiment expressed by the WAIN experts. Over 60% of the respondents joined the network for professional advice, mentoring and education. The item from the Phase 3 scale measuring opportunities and resources that scored the highest was also related to increasing professional knowledge. WAIN resources and opportunities provide technical and instrumental support for women in AI.

The new construct arising from Phase 2 results was social support provided by the network, offering social support rather than technical support. The social support construct from the expert panel in Phase 2 includes providing a safe space for women, a sense of belonging, role models and allies, recognition and advocacy, thus providing emotional security where members feel heard. Social support also includes providing advice through peers and mentors and being able to count on other network members. With this research phase being conducted at the tail end of the COVID-19 pandemic, the WAIN experts explained that the pandemic had positive consequences for WAINs. This finding is significant given the concerns about the widening gender gap due to the pandemic (Young, 2021, p. 26). In Phase 3, social support offered by the network was marginally positive, with the item "The network provides me with a safe space" scoring highest. Other researchers have found women-only networks to offer a safe space (Woodwark et al., 2021, p. 436). Although no literature was found in the context of WAINs, the importance of social support from networks was verified in other contexts, for example in a systematic review of social support and women's careers (Greer & Kirk, 2022, p. 8). Porter et al. (2023, p. 12) explain that "network contacts provide access to social support, coping resources, and heightened social exchange". Thus, social support from networking is beneficial for women in advancing and persisting in their careers. Primary research into social support in networks is a research recommendation from a recent study by (Greer & Kirk, 2022, p. 9).

How this behaviour translates into career persistence and advancement is a relationship examined in the final objective.

5.2.6. Research Objective 6

> *To determine the relationships between networking behaviour and career persistence and advancement*

From Phase 2, the model proposed direct relationships between networking behaviour and career advancement and career persistence, and indirect relationships via opportunities and resources and social support. This model was tested in Phase 3. The results emphasised the importance of networking resources, opportunities and social support, as these mediated the link between networking behaviour and career persistence and advancement. However, there were no significant direct relationships found. This finding is contrary to previous empirical research that found a direct

relationship between networking and career advancement, although this previous research was in the context of informal IT networks (Armstrong et al., 2018), rather than formal networks for women in AI. In a longitudinal study, Wolff and Moser (2009, p. 19) found that external networking was least important for direct network member career success, which is more in line with the results from this research. The lack of a significant direct relationship may be due to the network only being established recently, and the average length of membership being under 2 years. Research objective 6 was met by answering the associated research question below.

RQ6: *What are the relationships between networking behaviour and career persistence and advancement for women in AI?*

Significant indirect relationships were found between networking behaviour displayed by WAIN members and their career persistence and advancement in AI. Network social support was found to mediate the link to career advancement, while network opportunities and resources mediated the link to career persistence. Social support provides social or expressive support, while opportunities and resources provide technical or instrumental support, in line with findings by Porter et al. (2023, p. 32).

A new relationship between social support and opportunities and resources was found in Phase 3, providing evidence of serial mediation between networking behaviour and career persistence. Although not in the initial conceptual model based on theory, as described in Chapter 2, or suggested by the WAIN experts in phase 3, it does make sense that social support enhances the resources and opportunities offered by the network, especially as women can be hesitant in using networks (Greguletz et al., 2019, p. 26). Social support can encourage use of network resources and opportunities, for example uptake of training (Tokbaeva & Achtenhagen, 2023, p. 226). More research on how network social support can predict outcomes was recommended by Porter et al. (2023, p. 37). The supported relationships are shown in Figure 41 below:

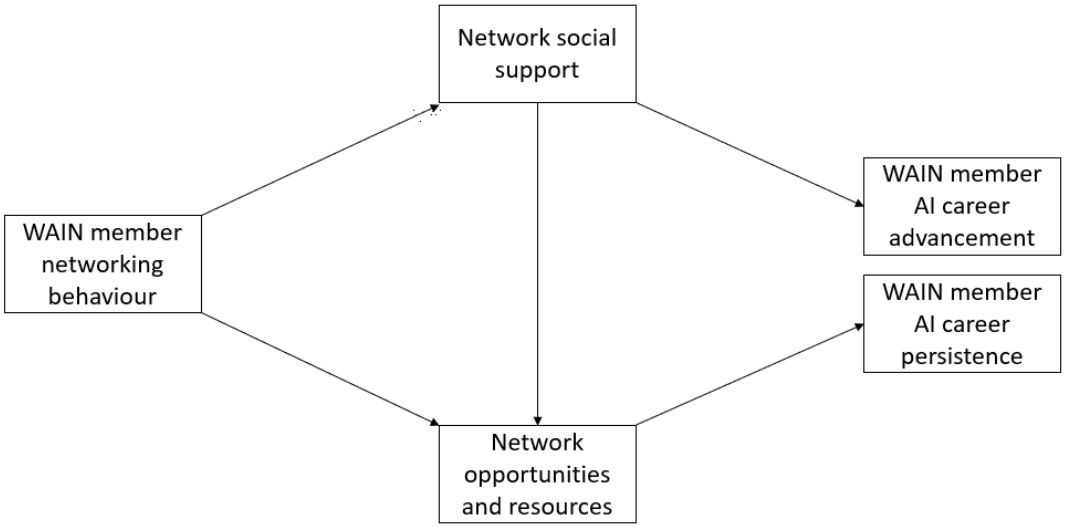

Figure 44 Final model with supported relationships

Figure 41 shows the final model of significant relationships between networking behaviour and career persistence and advancement for women in AI. The model had good fit and shows how social support and opportunities and resources mediate the relationships between networking behaviour and career persistence and advancement. Overall, the model presents novel findings from the study illustrating the importance of social support, particularly for career advancement. Interestingly, no significant relationship was found between opportunities and resources and career advancement, reiterating the importance of social or relational support for WAINs over technical or instrumental support for both career advancement and persistence.

5.3. Contributions

5.3.1. Theoretical contribution

Firstly, the systematic review in Phase 1 contributed to the body of knowledge by presenting the research on AI using a socio-technical framework, which is more valuable and should be the key focus rather than a more typical technical focus (Schwartz et al., 2022, p. 11; Singh et al., 2020, p. 1285). The socio-technical framework illustrates the importance of viewing issues such as AI bias from both a social and technical viewpoint, which is substantiated by Favaretto et al. (2019). However, the results of this review show that most previous research has focused on

the technical aspects only, which is a narrow approach that has drawn criticism (Whittaker et al., 2018, p. 11). While the success of AI systems requires a combined socio-technical perspective, the human or social side should be the driver (Singh et al., 2020, p. 1285). The review also showcased the current state of research on the causes and consequences of AI gender bias and the potential solutions. Interestingly, many of the emerging solutions from this review have been the subject of calls for further research (Dillon & Collett, 2019, p. 27; UNESCO, 2020, p. 34) and action, indicating the need to pursue these social solutions (Cowgill et al., 2020, p. 4). The results support the importance of considering gender in AI design and development teams explained by previous researchers (Roopaei et al., 2021, p. 498; Schulenberg et al., 2023, p. 183), which provided an impetus for solutions proposed in this research.

Secondly, this study provides a novel perspective on women-only networking in the AI profession as a means to improve gender representation in the field. The findings reveal that the opportunities and resources and social support provided by WAINs contribute to women persisting and advancing in AI. This finding aligns with recommendations by Roopaei et al. (2021, p. 500) for exploring and establishing an AI mindset through social support, such as role models, and opportunities and resources, such as skill development. Additionally, the research provided support for recommendations by Porter et al. (2023, p. 37) into how network social support can predict career outcomes. Phases 2 and 3 of this research show that WAINs provide a safe space where women feel heard, providing the social support necessary for women's subjective career success. The study highlights the importance of a gender-based perspective, thus answering the call for more research into gender in IT, and supports and extends the research by Gorbacheva et al. (2019, p. 49). Further, to achieve the UN's sustainable development goal of gender equality, more research is needed to assess the impact of algorithms on women and gender minorities (Vinuesa et al., 2020, p. 3). This research addresses this need by considering consequences and solutions of AI gender bias.

Thirdly, this research provides a new conceptual model based on theory, refined and extended by a WAIN expert panel and then tested in an empirical study. The model combined aspects from two theories specifically designed for women in IT and one on networking behaviours (Ahuja, 2002; Trauth et al., 2004; Wolff & Spurk, 2020). Elements of each theory applicable to women in AI and external professional networks

were combined, and relationships between them were proposed. The relationships proposed are supported in recent research by Porter et al. (2023), who surmised that information, influence and advice from networking, results in improved career success and professional advancement. Further, explicit or strategic networking motives enable career-benefiting resources (Kim, 2013, p. 123; Porter et al., 2023, p. 8), aligning with the proposition that network opportunities and resources mediate the link between networking behaviour and career persistence and advancement. A new concept not in the original conceptual model arose - that of social support offered by the network. Introducing this concept added balance to the model, consistent with the socio-technical framework used in Phase 1. Interestingly, social support emerged from the expert panel's initial evaluation of the theoretical model as important, and the results of Phase 3 substantiated their intuition.

The original model had mentorship and role models as a mediating construct. However, similar to research by Armstrong et al. (2018, p. 18), mentorship was subsumed into the broader constructs of support and opportunities and resources. Interestingly, the experts suggested gender and professional identity, from the initial theoretical model, do not play a moderating role in the relationship between networking behaviour and network members' AI careers. The new construct of social support may account for the deemphasis on gender identity since social support provides a sense of belonging and safe space.

Fourthly, this research provides a depth of understanding of concepts on networking and women in AI careers from the perspective of leaders and experts on women in AI. This research answers the call for further study into women-only networks, ideas to improve diversity and inclusion in AI development teams, and a focus on non-technical factors in AI bias (Annabi & Tari, 2018; Gorbacheva et al., 2019; West et al., 2019). The experts confirmed that women in AI face barriers in the workplace, preventing them from persisting and advancing in AI careers. Further, the experts agreed that the lack of women in AI translates into more biased AI solutions. Both of these align with existing recent research (e.g. Roopaei et al., 2021; Schulenberg et al., 2023; Schwartz et al., 2022). Also from the social perspective, the WAIN experts expanded the mentorship and role models construct to include allies, sponsors and other advocates. This research extends the existing body of knowledge on the importance of this social

support (e.g. Dashper, 2019, p. 19; Kim, 2013, p. 122; Roopaei et al., 2021, p. 498; Woehler et al., 2021, p. 215).

The experts provided insight into member networking behaviour. Although networking can go through sequential phases of building, maintaining and leveraging, this research showed how many behaviours exhibited by the WAIN members cross these boundaries and that the behaviour can be iterative, similar to findings by Kim (2013, p. 132). In addition, the more active WAIN members are, the more they will benefit from the resources and opportunities provided by the network. The WAIN experts exposed these resources and opportunities as wide-ranging, providing both breadth and depth of benefits for instrumental and social support. Opportunities and resources include access to current knowledge on AI, job opportunities and other work-related abilities which support members in their career development. The support and opportunities and resources mediating constructs broadly align with the informational, developmental and relational mechanisms necessary for career success (Bagdadli & Gianecchini, 2019, p. 364). The study provides theorisation, exploration and empirical research into formal woman-only networks, of which little was known previously (Villeseche & Josserand, 2017).

Fifthly, this research provided empirical evidence of the relationships between WAIN member networking behaviour and their career persistence and advancement in AI. The framework and research propositions arising from the qualitative Phase 2 were tested quantitatively with WAIN members. The research supports calls for empirical research into how women-only networks benefit members (Annabi & Tari, 2018, p. 5151), particularly in career development (Villeseche & Josserand, 2017, p. 14). The results evidenced that women join WAINs for technical or instrumental resources, including professional advice, education and job opportunities, and social or relational support, including connection, mentorship and belonging. The separation of the expressive (social) and instrumental (resources and opportunities) support offered by professional networks was also found in research by Porter et al. (2023, p. 39). By using an international WAIN that includes multiple nationalities and ethnicities, this research is more generalisable than other studies on networking limited to a specific country or context (e.g. Fryczyńska & Ivanova, 2019, p. 224; Woodwark et al., 2021, p. 420).

Further, the network resources, opportunities and social support mediate the relationship between networking behaviour and WAIN members' careers, rather than a direct relationship. Porter et al. (2023) also found an indirect relationship, although their research considered other mediators and was on professional networks in general. However, most previous research on networking and careers found a direct connection (Wolff & Moser, 2009, p. 17), although the networks studied were not gender or profession-specific, which could account for the discrepancy (Wanigasekara et al., 2022, p. 26). Phase 3 of the research provides a specific novel contribution in the finding that social support facilitated career advancement and, through serial mediation, career persistence. In contrast, network resources and opportunities facilitated WAIN member career persistence. These are new findings that contradict previous research suggesting a more direct relationship, explained above. Additionally, this research makes a specific contribution to networking research in the context of women-only networks in the AI profession. While literature on women-only networks exists, there is little research on WAINs and their contribution to career persistence and development.

Lastly, and perhaps most importantly, all phases of this research answer calls for more research into methods of supporting inclusivity in AI, from government to international organisations (Avila et al., 2018, p. 2; Gorbacheva et al., 2019, p. 50; Roopaei et al., 2021, p. 502). Specifically, this research answers the call for more research on women in IT career advancement and opportunities from professional networks (Armstrong et al., 2018, p. 19). The study builds on the existing body of knowledge on networking and careers, using a gender and AI lens. Existing studies reflect on the importance of networking but without the specific context provided in this research. This study is one of the first to gain a deep understanding of WAINs and how they support women in AI careers. The findings revealed the elements of networks that support women in persisting and advancing in their careers in AI. Although no direct relationship was found between networking behaviour and career persistence and advancement, this study highlights the role that opportunities and resources and social support play in mediating the relationship. The research, therefore, builds on the current research on networking and careers, offering additional insight into the relationships between WAIN member network behaviour and women in AI careers in support of increasing gender diversity in AI. The research answers the call for more representative AI development teams as a potential solution to reducing gender bias in AI. The conceptual model

combined theories to extend, verify and apply a conceptual framework relevant to women in AI, thus contributing to the academic body of knowledge.

5.3.2. Methodological contribution

The study contributes methodologically, demonstrating how a phased approach can add value to the development and adaption of a model, which adds to the robustness of the findings. The multi-phase sequential research design increases the research contribution, as the model was tested qualitatively, then quantitively, and was grounded in theory and data (Ivankava et al., 2007, p. 265). The conceptual model was based on theory, refined by WAIN experts and tested by WAIN members providing a framework relevant to women in AI, and contributing to the academic body of knowledge. Starting with a systematic review provided credibility and justification for the need for the research, providing impetus for the further sequential phases. The data analysis results from one phase connected with the data collection in the next phase.

A further methodological recommendation from this research relates to the PhD process itself. This thesis started out as a PhD by publication, which has the advantage of considering outcomes from the research that can make a real difference in the domain of interest. All traditional research stages, including a thorough literature review, development of a conceptual framework, detailed methodology, write up of findings, interpretation and discussion of results and synthesis of conclusions and recommendations are still needed in this format. While requirements for PhDs by Publication requirements vary by university, they all require the previously mentioned steps to the research process, in addition to publication of multiple papers at the time of submission. These papers are accompanied by Introductory (Introduction, Literature Review and Methodology) and Synthesis, Conclusion and Recommendations (Synthesis of Findings, Discussion, Conclusions and Recommendations) chapters.

However, the PhD by Publication route is relatively unknown, and this creates internal delays, for example in proposal review and approval and ethical clearance for each phase. The delays were acknowledged as being due to a lack of familiarity of this

approach and structure amongst reviewers, rather than being due the robustness of the research. Additionally, there are external delays that hinder this approach. The journal review processes can also take a very long time, particularly in highly reputable and sought-after journals. These internal and external delays led to the current research being submitted as a traditional monograph because university requirements are that the papers must already have been published at the time of submission for examination. Thus, a methodological recommendation from this research is a combined approach to the PhD process, where the PhD is planned as a PhD by Publication with a series of research outputs planned at the proposal and research design stage. These outputs should still support addressing an overarching research problem and purpose, and may present the findings related to one or more research objectives. However, the write up of the research and submission of the thesis for examination should be in the monograph format so that publication delays do not hold up the process, requiring additional fees and time.

5.3.3. Practical contribution

As AI becomes ubiquitous in business and society, potential solutions for reducing AI gender bias are valuable for national and international bodies concerned about the issue. In addition, the recent rise of transformer models and generative AI has increased the imperative to reduce gender bias (Nemani et al., 2023, p. 1). For example, the United Nations sustainability development goals include gender equity (Goal 5), but AI exacerbates gender discrimination due to a lack of diversity in the AI workforce (Schulenberg et al., 2023, p. 183; Vinuesa et al., 2020, p. 3). This research offers insights into how networking can assist women in AI, which relates to UNESCO's policy area 6 on gender, specifically item 92, to promote gender diversity in AI (UNESCO, 2021, p. 32). Further, the results of this research address UNESCO's inclusiveness in AI design goal (UNESCO, 2020, p. 14). The WEF (2018, p. 30) are similarly concerned about the gender gap in the AI profession and are looking to find ways to revise the trend and ensure more equity in the AI field so that AI systems better service society. Recommendations for how WAINs can be supported as potential tools to support women in AI is provided in the recommendation section below.

Governments worldwide have prioritised AI policies and regulations that include mitigating bias. Recently, the 'World cup of AI policy' was held, with the AI safety

summit bringing together governments from around the world, including important player such as China, the UK and US (Lazzaro, 2023, p. 1). The Organization for Economic Cooperation and Development (OECD, 2019, p. 90) and UNESCO (2020, p. 29) emphasise that public policy should include such mitigation practices. In developing African countries, Gwagwa, Kraemer-Mbula, Rizk, Rutenberg, and De Beer (2020, p. 7) contend that gender equity is at the heart of inclusion policies where multidimensional inequities result in women in Africa being marginalised. Similar recommendations are proposed for the G20 governments to be proactive in including women in the AI workforce (Avila et al., 2018, p. 2). The systematic review in Phase 1, Paper 1 of this research, established that firstly, gender bias can be caused by a lack of diversity in AI teams. Secondly, the consequences of AI gender bias include discrimination and harmful stereotypes. Thirdly, that AI gender bias can be mitigated by encouraging women to persist and advance in AI. Increasing gender representation in AI is at the heart of this research. Recommendations for how policy can support WAINs is provided in section 5.4 below.

This research can assist the AI industry in retention initiatives since the results show that networking resources, opportunities and support contribute to women persisting in their AI careers. Armstrong et al. (2018, p. 20) also suggested encouraging network events involvement for HR retention for women in IT. Additionally, facilitating external networking in WAINs will provide social support that can assist women in advancing in AI, which is important since the gender gap in AI is particularly noticeable at the leadership level (Avila et al., 2018, p. 31). Since AI initiatives are being embraced by businesses of all sizes and types across multiple industries, and with the AI gender gap prevalent across the board (WEF, 2018, p. 30), the results of this research should be of interest to managers of these businesses. Recommendations for how the AI industry can support WAINs is provided in the recommendations section below.

Gender equity organisations and initiatives can also use these results, providing empirical support for networking as a tool to improve gender equality. Diversity improves innovation and will be needed to ensure societies are resilient in the face of changes (Adams & Khomh, 2020, p. 107). Similarly, leaders and organisers of women-only networks, particularly WAINs, can employ these results when seeking funding or sponsorship. Since most WAINs are non-profit, being able to provide the resources and opportunities this research showed as necessary requires financing. For example,

events, workshops and courses have tangible costs that must be covered even with WAIN volunteers providing services free of charge (WAI, 2021). This research provides evidence that WAINs support women in their AI careers and can thus be used to support requests for funding. Further recommendations are provided below.

Thus, understanding WAINs will assist women, businesses, industry and policymakers in improving diversity in AI development teams, thereby providing impetus to reducing gender bias in AI algorithms. Results can be applied by a variety of organisations - those concerned with AI and AI ethics, gender diversity and support for women in business.

5.4. Recommendations

This research examined women in AI, their careers, and networking behaviour. More women and gender minorities should be included in AI management and development teams to increase awareness of gender bias, improve AI solutions and advance diversity and inclusion (Smith & Rustagi, p. 26). Human oversight of algorithms in use, especially in critical decisions, is recommended (Köchling & Wehner, 2020, p. 836). Increasing diversity in development teams emerged as a leading solution; therefore, ways to advance women's careers in AI should be prioritised for further research (Leavy, 2018, p. 16; Roopaei et al., 2021, p. 502). This finding is significant given the structural and persistent gender inequality in AI (Young, 2021, p. 4). Ensuring stereotypes of the past are not perpetuated in the solutions of the future (Kochi, 2018, p. 6; OECD, 2019, p. 90) will require effort from business and society in the form of company and public policy with a focus on human-centric, ethical AI (OECD, 2019, p. 16). The study findings should be used by WAIN organisers, their sponsors, organisations and public policy makers, and go some way to improving support for women in the industry, more inclusivity in development teams, and ultimately more robust AI solutions. Based on the results, the following recommendations can be made for the various stakeholders.

5.4.1. Recommendations for national and international policy bodies

Women in AI networks should be supported and promoted by societal, international and national AI ethics initiatives as a pragmatic method to advance women in AI careers. This advancement will increase the quantity and quality of women in AI development teams, improving inclusivity and reducing bias in AI solutions. Governments should proactively collaborate with businesses to increase gender diversity in AI development and research (Avila et al., 2018, p. 3). National and international organisations interested in reducing gender inequality in general, and in AI specifically, should increase support and encourage WAINs. This support could be through sponsorship, partnerships and engagement with WAINs. International organisations such as UNESCO and OECD that have already prioritised gender equity and AI can provide instrumental support and acknowledgement of WAINs as a potential support mechanism. Through increased awareness, international organisations can raise the profile of WAINs which will increase their legitimacy and lead to further national and industry practical support. Various national policy initiatives on AI ethics and reducing algorithmic bias are also ongoing, for example the US president recently signed an executive order on AI (Lazzaro, 2023, p. 1). Regional support is important for the global South, for example several initiatives to support African AI policy have been initiated, with suggestions for collaborations within African AI networks (Gwagwa et al., 2020) aligning with recommendations of this research. National initiatives can support local chapters of WAINs through sponsorships, co-hosting events such as award ceremonies and providing resources such as training courses. Promoting membership and building awareness of WAINs in the country and local communities are also recommended.

5.4.2. Recommendations for businesses developing AI solutions

Businesses should support external professional networks designed for women in AI rather than focusing on internal or informal networking initiatives. This recommendation aligns with recommendations for networking support by organisations in the form of time and money (Forret, 2014, p. 12). Businesses, particularly larger multinational technology firms, should support WAINs financially and through non-tangible support and sponsorship. Companies should attempt to increase gender diversity in AI design and development teams as supported by other research,

particularly from an intersectional perspective (Schulenberg et al., 2023, p. 181). Businesses will benefit from more inclusive AI solutions that appeal to a diverse gender base, ultimately improving their bottom line (Ashcraft et al., 2016, p. 16; Olbrich et al., 2015, p. 768). Businesses with AI development teams should support women's networking efforts, as previous research shows that even simple interventions can improve women's networking outcomes (Bapna & Funk, 2021, p. 593). This research shows that support and opportunities provided by WAINs increase career persistence, which businesses should support as a method of reducing turnover (Annabi & Tari, 2018, p. 5152). Business support for WAINs may have better outcomes than internal inclusivity and diversity initiatives that are not always successful (Dobbin & Kalev, 2016, p. 52), thus support for WAINs is recommended as it may provide more fruitful. Support can be in the form of events to showcase women in AI role models, resources such as workshops and speaking opportunities for WAIN members. Several of the international WAINs have sponsorship and partnerships divisions whose mandate is to find business partners; thus a recommendation is for businesses, especially those in the AI industry, to seek out these mutually beneficial collaborations.

5.4.3. Recommendations for WAIN organisers and leaders

WAIN network leaders and organisations should continue to provide opportunities and resources through the network. Opportunities for job seekers, members seeking to improve their knowledge and those seeking access to the latest information are especially important. Similarly, access to educational resources, mentors and events are valued by members. WAINs should continue to offer this access and increase such opportunities when possible. The significance of social support for career advancement should not be underestimated, therefore, WAINs should be proactive in providing social support mechanisms and maintaining a supportive atmosphere. Similarly, showcasing women in AI role models and recognising achievements through awards are formal methods to encourage social support and provide a voice for members. WAIN organisers should also be cognizant of the network's more nuanced, informal social support in giving members a safe space and sense of belonging, which is important to network and member success (Corbett & Hill, 2015, p. 46). WAINs can provide more resources and support for their members by creating more opportunities for upskilling of the members by providing or hosting more workshops, hackathons and training courses. Another recommendation is for WAINs to be proactive in facilitating more job, event and speaking opportunities for members. Additionally, providing

mentorship programmes across more countries and promoting and showcasing member talents through more country-specific award events is recommended. These recommendations align with the findings of this research into how network resources, opportunities and social support can enhance WAIN member career persistence and advancement.

5.4.4. Recommendations for women in AI

Discrimination and other barriers experienced in the workplace can place a strain on women, which may result in them leaving the AI workforce. However, women who belong to WAINs show high satisfaction with their career progress and tend to have a high affiliation with AI as a career path. A key recommendation for women who wish to persist and advance in AI is to join one or more WAINs and use the breadth and depth of resources and opportunities offered. Through active participation in WAINs, women can gain knowledge, access to job offers and mentorship opportunities and be exposed to the latest thinking and information in the field. Further, even though women and gender minorities may not see value in the social support offered by WAINs, this support can be invaluable in advancing and persisting in AI. Thus, women in AI benefit from joining WAINs irrespective of where they are in their AI career journey, including founders interested in starting and growing their own businesses. WAIN members already established in their AI careers are encouraged to engage and be proactive, as this can facilitate their success and advancement in AI.

5.5. Limitations and Recommendations for Future Research

The main limitation of this research is that it does not allow for the more nuanced biases experienced by different women. When considering the intersection of gender, race and age, different types and degrees of bias are experienced by women and gender minorities, for example, in women of colour (Buolamwini & Gebru, 2018, p. 89). Future research should consider AI gender bias as a multidimensional issue (Gwagwa et al., 2020; Schulenberg et al., 2023, p. 183). Further research is needed to improve inclusivity for all groups (UNESCO, 2020) so that solutions take intersectionality into account. Regarding networking, several support groups have arisen, for example, the Black Women in AI network. Additionally, WAINs have established sub-groups, e.g.

Africa, and have ambassadors representing each country's interests (WAI, 2021). Future SEM analysis based on group differences regarding intersectionality with gender and ethnicity would provide insight into how networking can support women of colour and women in developing countries in AI careers, thereby adding more AI workforce diversity. Further nuanced research on other underrepresented groups in society is also needed, for example gender minorities.

Further, quantitative research is recommended based on a larger sample to improve generalisability. Multiple personalised requests to the sample did not achieve the desired sample size, a limitation of the Phase 3 research. Online surveys often elicit poor response rates (du Plooy-Cilliers et al., 2021, p. 170), thus, an alternative data collection method is recommended. The online survey as a source for data collection also has limitations in providing nuance, therefore, a follow-up in-depth analysis with a qualitative lens is recommended. In addition, sampling could be expanded to include more networks catering to the specific types of AI, for example, women in machine learning, women in data science and women in computer vision.

Additionally, a longitudinal study, similar in design to Wolff and Moser (2009, p. 7), is recommended to gauge changes in career persistence and advancement over time rather than the static snapshot this research provided. A longitudinal study that can track the relationship between networking and women's careers in AI over a few years would be useful, given the recency of WAINs.

This research offered a conceptual model for women and gender minorities in AI networks and the relationship between networking behaviour and their persistence and advancement in AI careers. With the rapid increase in AI being used in business and decision-making in all spheres, it is imperative to investigate all options for assisting women in their AI careers (Roopaei et al., 2021). While this research provides insight into the importance of the social support and opportunities offered by WAINs in supporting women's careers in AI, more research is needed to gain a deeper understanding of how these networks can grow and be supported in their mission of improving gender representation in the AI field.

5.6. Final Conclusion

Gender bias in AI solutions threatens to reduce AI's societal and business benefits while amplifying gender discrimination through feedback loops. With the proliferation of AI deployments and the integration of AI into automated decision-making, it is more important than ever to improve the diversity of AI development teams and thereby reduce bias and improve the robustness of AI solutions (Nadeem, Marjanovic, & Abedin, 2021; Roopaei et al., 2021). This research uniquely considers the role of networking in increasing gender diversity in the AI workforce by exploring WAINs and the support they offer in assisting women in AI career persistence and advancement. Further, this study is one of a few to map the current state of research on gender bias from a social perspective through a systematic review, where a case was made for increasing diversity in AI development teams to reduce gender bias in AI solutions. In a report proposing future research in AI and gender, Dillon and Collett (2019) recommend diversity in AI careers as a major research theme. The results of this research support the need for more research into ways of increasing the representation of women and gender minorities in AI development teams and leadership (Roopaei et al., 2021, p. 502; Schulenberg et al., 2023, p. 177).

This study helped to close the research gap identified – the relationship between networking behaviour in WAINs and career persistence and advancement for women in the AI profession. The model provides theoretical and empirical support for the mediating value of social support and opportunities and resources provided by WAINs. Notably, the value of social support was established. The research confirms literature on the importance of networking for career success but offers additional value in exploring the role of the opportunities and resources and the social support provided by the network. Further, the findings contribute to the study of networking behaviour in external professional networks by specifically looking at women-only AI networks. The results suggest that social support is essential in WAINs and provide insight into network opportunities and resources that are important to WAIN members in persisting and advancing in their careers.

Equally important were the findings that deviated from the expected. Firstly, no significant direct relationship between networking behaviour and member career

persistence or advancement was found, contrary to most literature, the initial model and the WAIN experts' expectations. Secondly, although the initial conceptual model and WAIN experts suggested networking behaviour would increase AI career advancement via the opportunities and resources provided, this relationship was not supported empirically. There are several possibilities for both these findings, for example, given the mean number of years of network membership at only 1.6, the networking efforts might not yet yield results in terms of career advancement or persistence. Furthermore, direct effects are less pronounced when intermediate factors are involved (Aten, DiRenzo, & Shatnawi, 2017, p. 474), as proved the case with this study. Another unexpected finding was the new relationship between social support and opportunities and resources which provided evidence of serial mediation between networking behaviour and AI career persistence, further emphasising the role of social support. The importance of social support adds value to research on WAINs and is helpful on a practical level for the organisers, sponsors and supporters of WAINs. Creating conditions for social support where women have a safe space and sense of belonging will improve the value of the network for women's careers and contribute to gender diversity in the AI workforce.

In general, WAINs should be supported by the AI industry, businesses developing AI solutions, national and international bodies concerned with AI ethics and gender equality and governments working on AI policy. The diversity of groups who could use the results and recommendations of this research point to the contribution the study makes from a practical viewpoint. Finally, this study contributes to the body of knowledge on AI gender bias, women in the AI workforce, and WAINs by providing a theoretically based, refined and tested model on networking behaviours and women's AI careers.

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Appendix A – Informed Consent Letters

UKZN HUMANITIES AND SOCIAL SCIENCES RESEARCH ETHICS COMMITTEE (HSSREC)

APPLICATION FOR ETHICS APPROVAL
For research with human participants

Information Sheet and Consent to Participate in Research

Date: 1 August 2021

Greetings,

My name is Paula Hall, PhD candidate from UKZN, School of Management, Information Technology and Governance, Contact number +2777 709 7099, 871871741@stu.ukzn.ac.za.

You are being invited to consider participating in a study that involves research into women in AI networks. The aim and purpose of this research is to determine the benefits of women in AI networks and the impact on members' careers. This preliminary study is expected to include 6 participants who hold a leadership position in a Women in AI network. It will involve an online interview of approximated half an hour.

The study holds no known risks and/or discomforts. We hope that the study will create the benefit of providing insight into the benefits of AI networks, developing a model on the link between networking and network member careers. An alternate option to the live interview is to answer the interview questions via email or an online form.

This study has been ethically reviewed and approved by the UKZN Humanities and Social Sciences Research Ethics Committee (approval number HSSREC/00003346/2021).

In the event of any problems or concerns/questions you may contact the researcher at 871871741@stu.ukz.ac.za or +2776 709 7099 or 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

Your participation in the study is voluntary and by participating, you are granting the researcher permission to use your responses. You may refuse to participate or withdraw from the study at any time with no negative consequence. Your anonymity will be maintained by the researcher and the School of Management, I.T. & Governance and your responses will not be used for any purposes outside of this study.

All data, both electronic and hard copy, will be securely stored during the study and archived for 5 years. After this time, all data will be destroyed.

If you have any questions or concerns about participating in the study, please contact me or my research supervisor using the contact details contained in this letter.

Sincerely

Paula Hall

Research supervisor: Prof Debbie Ellis
Email: vigard@ukzn.ac.za
Phone: +27828988952

CONSENT TO PARTICIPATE

I (Name) have been informed about the study entitled Exploring the effects of Women in Artificial Intelligence Networks (WAINs) on women's careers in Artificial Intelligence by Paula Hall.

I understand the purpose and procedures of the study.

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 at (provide details) 871871741@stu.ukz.ac.za or +2776 709 7099.

If I have any questions or concerns about my rights as a study participant, or if I am concerned about an aspect of the study or the researchers then I may contact:

HUMANITIES & SOCIAL SCIENCES RESEARCH ETHICS ADMINISTRATION
Research Office, Westville Campus
Govan Mbeki Building
Private Bag X 54001
Durban
4000
KwaZulu-Natal, SOUTH AFRICA
Tel: 27 31 2604557 - Fax: 27 31 2604609
Email: HSSREC@ukzn.ac.za

Additional consent, where applicable

I hereby provide consent to:

Record my interview YES / NO

_____ _____

Signature of Participant **Date**

Appendix B – Gatekeeper's Letter

Gatekeeper's Consent
Research Title: Exploring the effects of Women in Artificial Intelligence Networks (WAINs) on women's careers in AI
I Marisa Tschopp…….…….. in my capacity as WAI Ambassador and CRO…….…….hereby give permission to Paula Hall (Student No. 871871741) to conduct research in the Women in AI organization.
The data may be collected at: (please indicate the research site)
womeninai.co……...
The student MAY/ use the name of the organisation in the dissertation.
Additional conditions for granting permission to conduct research:
……
……
……
……
Signature of Manager/Owner/Gatekeeper:[redacted]**……**
Email: mats@scip.ch……
Phone: 0041766808784……
Address: Farnstrasse 9, 5507……
Company Stamp:

Date: 23.6.2022……

Appendix C – Interview Schedule and Questionnaire

Interview schedule used in Phase 3

Introduction

Thank you for your time in participating in this interview on Women in AI and women in AI networks. Your expertise and honest answers are greatly appreciated. It should take approximately an hour. Please sign the attached informed consent letter. Your confidentiality is ensured.

Questions relating to women in AI

1. Please explain your history in the AI profession.
2. Do you believe it is a problem that there are so few women in AI? If so, why?
3. Why do you think there are even fewer women in the AI field than there are women in the general IT field?
4. What advantages do you think women bring to AI development teams?
5. Why do you think women are more likely to leave the AI profession than men?
6. Why do you believe there are so few women in leadership and higher paying roles in AI?
7. What do you believe women can do to advance in AI careers?

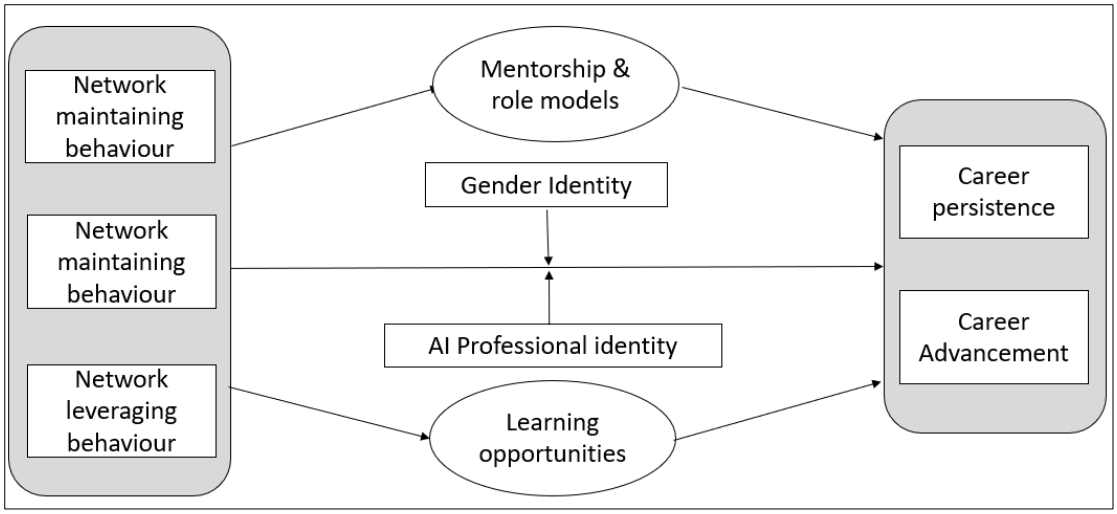
Questions relating to women in AI Networks

1. Please describe your current role/s in Women in AI network/s
2. What do you think the main services are that the network offers to its members?
3. What do you think the top five benefits of belonging to the network are?
4. What feedback have you had from members as to why they join the network?
5. What are the benefits of belonging to a women-only network?
6. How do you think the network would be different if it weren't women only?
7. What are the benefits of belonging to a network specific to the AI field?
8. How do you think the network would be different if it were for the general IT field?
9. What should members do to build up their network?
10. What should members do to maintain their network?
11. What should members do to leverage their network contacts?
12. How do you think the network assists members in **advancing** in their careers? Please list as many ways as you can think of
13. What else can the network offer that could help women advance in the AI field?
14. What does the network offer that encourages women to **remain** in the AI field? Please list as many ways as you can think of
15. What else could the network offer to help women remain in the AI field?

Personal characteristics and opportunities in women in AI networks

1. Do you think gender identity plays a role in how much members get out of the network? If so, how?
2. Do you think professional identity plays a role in how much members get out of the network? If so, how?
3. How do you think members identify with the AI profession specifically, rather than to general IT?
4. Do you think member's AI professional identity plays a role in how much members get out of the network? If so, how?
5. What mentorship opportunities does the women in AI network offer?
6. What benefits do you think members get if they make use of the mentorship?
7. What benefits do you think having role models in the women in AI network offers to members?
8. What opportunities to learn does the network offer?
9. What benefits do you think members get if they make use of learning opportunities offered?
10. Are there any other personal characteristics you can think of that allow members to get more out of the network?
11. Are there any other learning opportunities offered by the network that may benefit members?

Please give your opinion on the initial model below, developed from theory. I will explain the model, if you could please give your opinion on the main features and relationships.



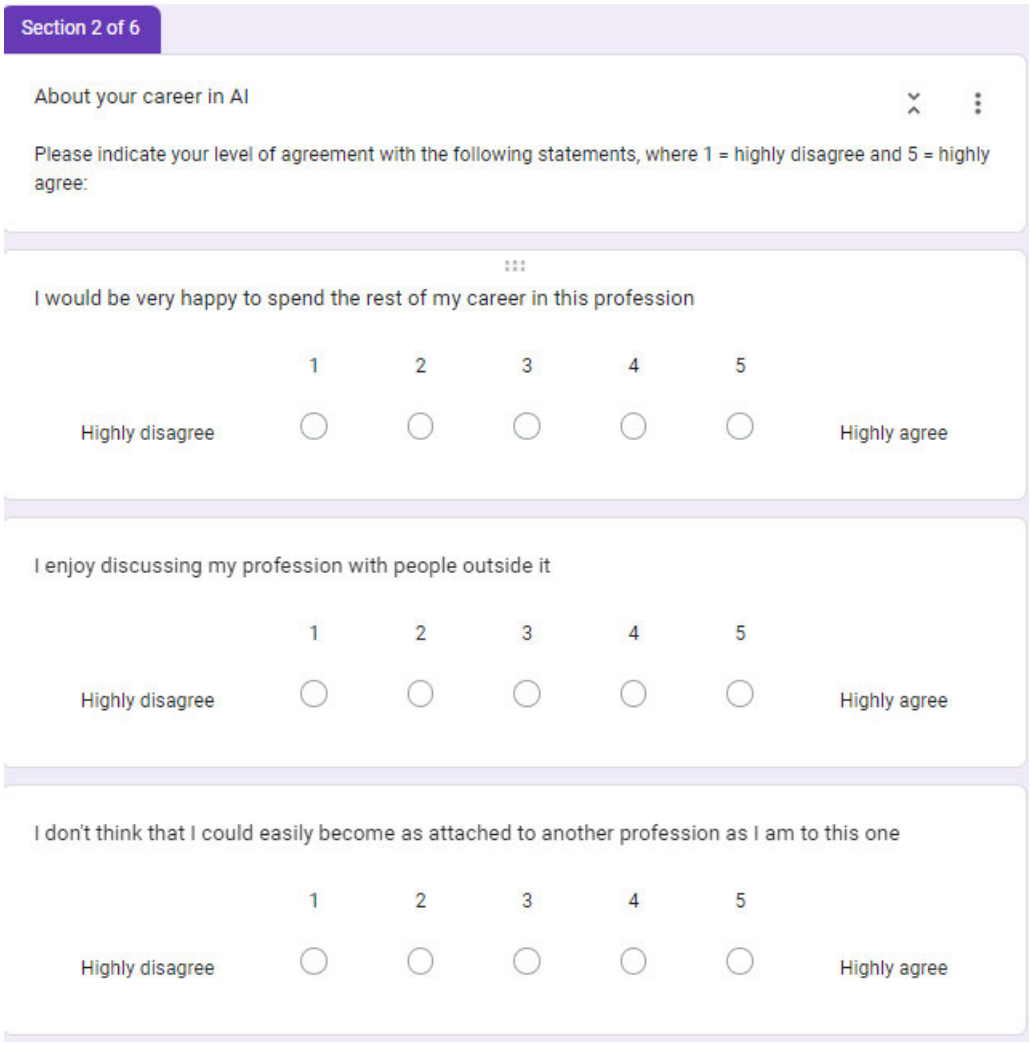
- The more networking behaviour displayed by WAIN members, the stronger their career persistence and advancement.

- Gender identity moderates the relationship between network behaviour of WAIN members and their AI career persistence and advancement.
- AI professional identity moderates the relationship between network behaviour of WAIN members and their AI career persistence and advancement.
- Support from WAIN Mentors and role models mediates the relationship between networking behaviour and their AI career persistence and advancement.
- WAIN learning opportunities take-up mediates the relationship between WAIN member networking behaviour and their AI career persistence and advancement.

Conclusion

Thank you for your valuable time. I would like to review the updated model with you, after changes have been made based on your responses to the questions in this interview.

Questionnaire used in Phase 4



Section 2 of 6

About your career in AI

Please indicate your level of agreement with the following statements, where 1 = highly disagree and 5 = highly agree:

I would be very happy to spend the rest of my career in this profession

	1	2	3	4	5	
Highly disagree	○	○	○	○	○	Highly agree

I enjoy discussing my profession with people outside it

	1	2	3	4	5	
Highly disagree	○	○	○	○	○	Highly agree

I don't think that I could easily become as attached to another profession as I am to this one

	1	2	3	4	5	
Highly disagree	○	○	○	○	○	Highly agree

I feel 'emotionally attached' to this profession

	1	2	3	4	5	
Highly disagree	○	○	○	○	○	Highly agree

I feel a strong sense of belonging to my profession

	1	2	3	4	5	
Highly disagree	○	○	○	○	○	Highly agree

I am satisfied with the success I have achieved in my career

	1	2	3	4	5	
Highly disagree	○	○	○	○	○	Highly agree

I am satisfied with the progress I have made towards meeting my overall career goals

	1	2	3	4	5	
Highly disagree	○	○	○	○	○	Highly agree

I am satisfied with the progress I have made towards meeting my goals for income

	1	2	3	4	5	
Highly disagree	○	○	○	○	○	Highly agree

I am satisfied with the progress I have made towards meeting my goals for advancement

	1	2	3	4	5	
Highly disagree	○	○	○	○	○	Highly agree

I am satisfied with the progress I have made towards meeting my goals for the development of new skills

	1	2	3	4	5	
Highly disagree	○	○	○	○	○	Highly agree

Please enter your job title

Short answer text

Section 3 of 6

How you network in Women in AI

Please indicate your level of agreement with the following statements, where 1 = highly disagree and 5 = highly agree:

I take on roles and tasks in the network which could also be useful to me professionally

	1	2	3	4	5	
Highly disagree	○	○	○	○	○	Highly agree

I develop informal contacts with professionals in the network, in order to have personal links

	1	2	3	4	5	
Highly disagree	○	○	○	○	○	Highly agree

I take part in network meetings and talks

	1	2	3	4	5	
Highly disagree	○	○	○	○	○	Highly agree

I am an active member the network

	1	2	3	4	5	
Highly disagree	◯	◯	◯	◯	◯	Highly agree

I accept invitations to network events

	1	2	3	4	5	
Highly disagree	◯	◯	◯	◯	◯	Highly agree

I meet with network members outside of regular working hours

	1	2	3	4	5	
Highly disagree	◯	◯	◯	◯	◯	Highly agree

When I obtain informal information that might be of importance to network members, I pass it on to them

	1	2	3	4	5	
Highly disagree	◯	◯	◯	◯	◯	Highly agree

I meet network members that could be of professional importance to me at casual get-togethers

	1	2	3	4	5	
Highly diasagree	○	○	○	○	○	Highly agree

I use my contacts in the network to ask for advice

	1	2	3	4	5	
Highly disagree	○	○	○	○	○	Highly agree

I use network events to talk to network acquaintances on a personal level

	1	2	3	4	5	
Highly disagree	○	○	○	○	○	Highly agree

I discuss business matters with network members after working hours

	1	2	3	4	5	
Highly disagree	○	○	○	○	○	Highly agree

If I meet network members, I approach them to catch up on news and changes in their professional lives

	1	2	3	4	5	
Highly disagree	○	○	○	○	○	Highly agree

I exchange professional tips and hints with network members

	1	2	3	4	5	
Highly disagree	○	○	○	○	○	Highly agree

When I hear of an interesting job opening, I contact network members for more information

	1	2	3	4	5	
Highly disagree	○	○	○	○	○	Highly agree

When I can't solve a problem at work I consult network members and ask for advice

	1	2	3	4	5	
Highly disagree	○	○	○	○	○	Highly agree

Approximately how many years have you been a member of a Women in AI network?

1. 0
2. 1
3. 2
4. 3
5. 4
6. 5
7. 6
8. 7
9. 8
10. 9
11. 10
12. More than 10

How many other networks are you a member of?

1. 0
2. 1
3. 2
4. 3
5. 4
6. 5
7. 6
8. 7
9. 8
10. 9
11. 10
12. More than 10

What is your main reason for belonging to your network?

- ○ Professional advice, mentoring and education
- ○ Job, speaking and promotional opportunities
- ○ Personal, emotional and social support
- ○ Other

Section 4 of 6

Support from the network

Please indicate your level of agreement with the following statements, where 1 = highly disagree and 5 = highly agree:

I have relationships in the network where my competence and skills are recognized

	1	2	3	4	5	
Highly disagree	○	○	○	○	○	Highly agree

I have relationships in the network that provide me with a sense of emotional security and well-being

	1	2	3	4	5	
Highly disagree	○	○	○	○	○	Highly agree

There are people in the network who admire my talents and abilities

	1	2	3	4	5	
Highly disagree	○	○	○	○	○	Highly agree

There are people in the network I could talk to about important decisions

	1	2	3	4	5	
Highly disagree	○	○	○	○	○	Highly agree

There are people in the network I could turn to for advice if I were having problems

	1	2	3	4	5	
Highly disagree	○	○	○	○	○	Highly agree

There are people in the network I can count on

	1	2	3	4	5	
Highly disagree	○	○	○	○	○	Highly agree

There are people in the network who will advocate for me

	1	2	3	4	5	
Highly disagree	○	○	○	○	○	Highly agree

The network provides me with a sense of belonging

	1	2	3	4	5	
Highly disagree	○	○	○	○	○	Highly agree

The network provides me with a safe space

	1	2	3	4	5	
Highly disagree	○	○	○	○	○	Highly agree

The network provides me with a voice

	1	2	3	4	5	
Highly disagree	○	○	○	○	○	Highly agree

My network provides mentorship qualities by giving me specific strategies for achieving career aspirations

	1	2	3	4	5	
Highly disagree	○	○	○	○	○	Highly agree

My network provides mentorship qualities by giving me advice on how to attain recognition

	1	2	3	4	5	
Highly disagree	○	○	○	○	○	Highly agree

My network provides mentorship qualities by giving me help me to learn about other parts of the organization

	1	2	3	4	5	
Highly disagree	○	○	○	○	○	Highly agree

My network provides mentorship qualities by giving me role models

	1	2	3	4	5	
Highly disagree	○	○	○	○	○	Highly agree

My network provides mentorship qualities by giving me examples of who I want to be

	1	2	3	4	5	
Highly disagree	○	○	○	○	○	Highly agree

My network provides mentorship qualities by giving me examples whom I identify with

	1	2	3	4	5	
Highly disagree	○	○	○	○	○	Highly agree

Section 5 of 6

Network opportunities

Please indicate your level of agreement with the following statements, where 1 = highly disagree and 5 = highly agree:

My network provides opportunities to connect with sponsors

	1	2	3	4	5	
Highly disagree	◯	◯	◯	◯	◯	Highly agree

My network provides opportunities to connect with collaborators

	1	2	3	4	5	
Highly disagree	◯	◯	◯	◯	◯	Highly agree

I receive a high level of career support from my network

	1	2	3	4	5	
Highly disagree	◯	◯	◯	◯	◯	Highly agree

My network supports me in my career development

	1	2	3	4	5	
Highly disagree	○	○	○	○	○	Highly agree

I regularly collect information about career opportunities through my network

	1	2	3	4	5	
Highly disagree	○	○	○	○	○	Highly agree

I constantly stay up-to-date about employment opportunities in the labor market through my network

	1	2	3	4	5	
Highly disagree	○	○	○	○	○	Highly agree

My network provides opportunity to expand my professional knowledge

	1	2	3	4	5	
Highly disagree	○	○	○	○	○	Highly agree

My network develops my work-related abilities

	1	2	3	4	5	
Highly disagree	○	○	○	○	○	Highly agree

My network helps ensure that my work-related abilities and knowledge are up-to-date

	1	2	3	4	5	
Highly disagree	○	○	○	○	○	Highly agree

My network provides events/talks/conferences/summits for learning and networking

	1	2	3	4	5	
Highly disagree	○	○	○	○	○	Highly agree

My network provides courses/classes/workshops for learning

	1	2	3	4	5	
Highly disagree	○	○	○	○	○	Highly agree

My network provides opportunities for learning soft skills

	1	2	3	4	5	
Highly disagree	○	○	○	○	○	Highly agree

My network provides me with speaking opportunities

	1	2	3	4	5	
Highly disagree	○	○	○	○	○	Highly agree

My network provides me with volunteering opportunities

	1	2	3	4	5	
Highly disagree	○	○	○	○	○	Highly agree

My network provides me with self-promotion opportunities

	1	2	3	4	5	
Highly disagree	○	○	○	○	○	Highly agree

The network provides me opportunities to increase my eminence in the AI profession

	1	2	3	4	5	
Highly disagree	○	○	○	○	○	Highly agree

My network provides me with opportunities to showcase/celebrate my skills/achievements

	1	2	3	4	5	
Highly disagree	○	○	○	○	○	Highly agree

My network provides me with opportunities for receiving awards

	1	2	3	4	5	
Highly disagree	○	○	○	○	○	Highly agree

What is the main benefit of the network for you?

Short answer text

Section 6 of 6

Last few questions: your background

Please answer the following questions. Select one answer from the options provided.

Please indicate your age group:

- under 21
- 21-30
- 31-40
- 41-50
- 51-60
- Over 60

Highest education level

- Secondary school not completed
- Secondary school completed
- Tertiary completed
- Post-graduate completed

Please indicate the your educational background

- ○ Not applicable
- ○ More than one
- ○ Arts
- ○ Classics
- ○ Economics
- ○ Education
- ○ Engineering
- ○ Humanities
- ○ Information Technology
- ○ Law
- ○ Management
- ○ Music
- ○ Natural Science
- ○ Philosophy
- ○ Pollical Science
- ○ Other...

What is your current employment status?

- ○ Self-employed
- ○ Employed full time (40 or more hours per week)
- ○ Employed part time (up to 39 hours per week)
- ○ Unemployed and currently looking for work
- ○ Unemployed and not currently looking for work
- ○ Student
- ○ Retired
- ○ Homemaker
- ○ Unable to work

Please indicate your gender identity

- ○ Female
- ○ Male
- ○ Transgender
- ○ Cisgender
- ○ Non-binary/third gender
- ○ Agender
- ○ Prefer to self-describe
- ○ Genderqueer
- ○ A gender not listed
- ○ Prefer not to say

Which category best describes you

- ○ American Indian or Alaska Native(Eg: Navajo nation, Blackfeet tribe, Mayan, Aztec, Native Village or Barr...
- ○ Asian (Eg: Chinese, Filipino, Asian Indian, Vietnamese, Korean, Japanese, etc)
- ○ Black (Eg: African, African American, Jamaican, Haitian, Nigerian, Ethiopian, Somalian, etc)
- ○ Hispanic, Latino or Spanish origin (Eg: Mexican or Mexican American, Puerto Rican, Cuban, Salvadoran, ...
- ○ Middle Eastern or North African (Eg: Lebanese, Iranian, Egyptian, Syrian, Moroccan, Algerian, etc)
- ○ Native Hawaiian or Other Pacific Islander (Eg: Native Hawaiian, Samoan, Chamorro, Tongan, Fijian, etc)
- ○ White (Eg: German, Irish, English, Italian, Polish, French, etc)
- ○ Some other race, ethnicity or origin
- ○ Prefer not to say

How many years of working experience do you have?

- 0
- 1 - 5
- 6 - 10
- 11 - 15
- 16 - 20
- 21 - 25
- 26 - 30
- 31 - 35
- 36 - 40
- More than 40

How many years have you been in the AI profession?

- 0
- 1
- 2
- 3
- 4
- 5
- 6
- 7
- 8
- 9
- 10
- more than 10

What is your current country of residence?

Short answer text

Thank you so much for your time! If you have any final comments, please make them below, otherwise click on the submit button.

Short answer text

Appendix D – Phase 4 Demographic Descriptives and Nonsignificant Group Differences

Age

Table 21 Frequency distributions for age group

Age group		
	N	%
21-30	87	42.2%
31-40	75	36.4%
41-50	33	16.0%
51-60	7	3.4%
Over 60	2	1.0%
under 21	2	1.0%

Ethnicity

Table 22 Ethnicity

Ethnicity		
	N	%
American Indian or Alaska Native(E.g.: Navajo nation, Blackfeet tribe, Mayan, Aztec, Native Village or Barrow Inupiat Traditional Government, Nome Eskimo Community, etc)	2	1.0%
Asian (E.g.: Chinese, Filipino, Asian Indian, Vietnamese, Korean, Japanese, etc)	60	29.1 %
Black (E.g.: African, African American, Jamaican, Haitian, Nigerian, Ethiopian, Somalian, etc)	25	12.1 %
Hispanic, Latino or Spanish origin (E.g.: Mexican or Mexican American, Puerto Rican, Cuban, Salvadoran, Dominican, Colombian, etc)	12	5.8%
Middle Eastern or North African (E.g.: Lebanese, Iranian, Egyptian, Syrian, Moroccan, Algerian, etc)	15	7.3%
Prefer not to say	7	3.4%

Some other race, ethnicity or origin	2	1.0%
White (E.g.: German, Irish, English, Italian, Polish, French, etc)	83	40.3 %

Gender identity

Table 23 Gender identity

Gender identity		
	N	%
Female	198	96.1%
Genderqueer	1	0.5%
Male	4	1.9%
Prefer not to say	1	0.5%
Prefer to self-describe	2	1.0%

Education

Table 24 Education Level

Education level		
	N	%
Post-graduate completed	146	70.9%
Secondary school completed	10	4.9%
Tertiary completed	50	24.3%

Table 25 Educational category

Education category		
	N	%
Arts	1	0.5%
Classics	1	0.5%

Computer Science	5	2.4%
Economics	9	4.4%
Education	5	2.4%
Engineering	59	28.6%
Humanities	11	5.3%
Information Technology	50	24.3%
Law	2	1.0%
Linguistics	1	0.5%
Management	8	3.9%
Mathematics	6	2.9%
More than one	22	10.7%
Natural Science	13	6.3%
Not answered	2	1.0%
Philosophy	3	1.5%
Political Science	4	1.9%
Psychology	1	0.5%
Social Science	3	1.5%

Country

Table 26 Country of residence

Country		
	N	%
Algeria	2	1.0%
Australia	5	2.4%
Austria	1	0.5%
Bulgaria	1	0.5%
Canada	17	8.3%
Colombia	1	0.5%
Denmark	1	0.5%
Ethiopia	4	1.9%

Finland	6	2.9%
France	9	4.4%
Germany	13	6.3%
Iceland	1	0.5%
India	10	4.9%
Indonesia	1	0.5%
Ireland	6	2.9%
Italy	7	3.4%
Japan	1	0.5%
Korea	1	0.5%
Malaysia	2	1.0%
Malta	1	0.5%
Mexico	5	2.4%
Montenegro	1	0.5%
Morocco	1	0.5%
Myanmar	1	0.5%
Nepal	2	1.0%
Netherlands	8	3.9%
Nigeria	8	3.9%
Not answered	10	4.9%
Pakistan	1	0.5%
Philippines	3	1.5%
Poland	3	1.5%
Spain	3	1.5%
Sudan	1	0.5%
Sweden	9	4.4%
Taiwan	1	0.5%
Tanzania	2	1.0%
Thailand	1	0.5%
Tunisia	1	0.5%
UAE	5	2.4%

UK	12	5.8%
United States	38	18.4%

Employment

Table 27 Employment status

Employment Status		
	N	%
Employed full time (40 or more hours per week)	129	62.6%
Employed part time (up to 39 hours per week)	16	7.8%
Self-employed	27	13.1%
Student	25	12.1%
Unemployed and currently looking for work	8	3.9%
Unemployed and not currently looking for work	1	0.5%

Table 28 Working years

Years working		
	N	%
0	5	2.4%
1-5	88	42.7%
10-15	1	0.5%
11-15	24	11.7%
16 - 20	19	9.2%
21 - 25	17	8.3%
26 - 30	6	2.9%
31 - 35	1	0.5%
36 - 40	3	1.5%
6-10	42	20.4%

Table 29 Job category

Job Category

	N	%
Academic	38	18.4%
AI Ethicist	7	3.4%
CEO	4	1.9%
Consultant	10	4.9%
Data Scientist	45	21.8%
Developer	13	6.3%
Founder	11	5.3%
Machine learning engineer	31	15.0%
Manager	16	7.8%
Marketing	4	1.9%
Not answered	16	7.8%
Top Manager	11	5.3%

Table 30 Years in AI profession

Statistics

Years_in_AI

N	Valid	206
	Missing	0
Mean		3.18
Std. Deviation		2.207

WAIN membership

Table 31 Years in the network

Years in network

N	Valid	206

Missing	0
Mean	1.62
Std. Deviation	1.436

Table 32 Reasons for joining the network

Reasons for joining network

	N	%
Job, speaking and promotional opportunities	52	25.2%
Other	8	3.9%
Personal, emotional and social support	22	10.7%
Professional advice, mentoring and education	124	60.2%

Results of analysis to determine if networking behaviour, and career persistence and advancement differs by membership length, age and gender identity showed no statistically significant results:

Differences by membership length

A one way between groups Anova test was performed to determine if networking behaviour was different depending on the number of years members had been in the WAIN. No statistically significant result was found.

Networking behaviour and years in the network

ANOVA

Network Behaviour

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	1.020	8	.128	.224	.986
Within Groups	112.104	197	.569		
Total	113.124	205			

Networking behaviour and age group

The Kruskal-Wallis H test showed that there was no statistically significant difference in networking behaviour based on age group.

Networking behaviour and age

Test Statistics[a,b]

	Network Behaviour
Kruskal-Wallis H	3.749
df	5
Asymp. Sig.	.586

a. Kruskal Wallis Test

b. Grouping Variable: age

Networking behaviour and gender identity

The Kruskal-Wallis H test showed that there was no statistically significant difference in networking behaviour based on member's gender identity.

Test Statistics[a,b]

	Network Behaviour
Kruskal-Wallis H	9.156
df	6
Asymp. Sig.	.165

a. Kruskal Wallis Test

b. Grouping Variable: identity

Appendix E – Ethical Clearance

UNIVERSITY OF KWAZULU-NATAL
INYUVESI YAKWAZULU-NATALI

14 February 2021

Ms Paula Hall (871871741)
School Of Man Info Tech & Gov
Pietermaritzburg Campus

Dear Ms Hall,

Protocol reference number: HSSREC/00002352/2021
Project title: Exploring the effects of Women in Artificial Intelligence Networks (WAINs) on women's careers in AI
Degree: PhD

Approval Notification – Expedited Application

This letter serves to notify you that your application received on 13 November 2020 in connection with the above, was reviewed by the Humanities and Social Sciences Research Ethics Committee (HSSREC) and the protocol has been granted **FULL APPROVAL**.

Any alteration/s to the approved research protocol i.e. Questionnaire/Interview Schedule, Informed Consent Form, Title of the Project, Location of the Study, Research Approach and Methods must be reviewed and approved through the amendment/modification prior to its implementation. In case you have further queries, please quote the above reference number. PLEASE NOTE: Research data should be securely stored in the discipline/department for a period of 5 years.

This approval is valid until 14 February 2022.
To ensure uninterrupted approval of this study beyond the approval expiry date, a progress report must be submitted to the Research Office on the appropriate form 2 - 3 months before the expiry date. A close-out report to be submitted when study is finished.

All research conducted during the COVID-19 period must adhere to the national and UKZN guidelines.

HSSREC is registered with the South African National Research Ethics Council (REC-040414-040).

Yours sincerely,

[redacted]

Professor Dipane Hlalele (Chair)

/dd

Humanities and Social Sciences Research Ethics Committee
Postal Address: Private Bag X54001, Durban, 4000, South Africa
Telephone: +27 (0)31 260 8350/4557/3587 **Email:** hssrec@ukzn.ac.za **Website:** http://research.ukzn.ac.za/Research-Ethics
Founding Campuses: Edgewood Howard College Medical School Pietermaritzburg Westville

UNIVERSITY OF KWAZULU-NATAL
INYUVESI YAKWAZULU-NATALI

23 September 2021

Ms Paula Hall (871871741)
School Of Man Info Tech & Gov
Pietermaritzburg Campus

Dear Ms Hall,

Protocol reference number: HSSREC/00003346/2021
Project title: Exploring the effects of Women in Artificial Intelligence Networks (WAINs) on women's careers in Artificial Intelligence
Degree: PhD

Approval Notification – Expedited Application

This letter serves to notify you that your application received on 18 September 2021 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.

This approval is valid until 23 September 2022.
To ensure uninterrupted approval of this study beyond the approval expiry date, a progress report must be submitted to the Research Office on the appropriate form 2 - 3 months before the expiry date. A close-out report to be submitted when study is finished.

All research conducted during the COVID-19 period must adhere to the national and UKZN guidelines.

HSSREC is registered with the South African National Research Ethics Council (REC-040414-040).

Yours sincerely,

[redacted]

Professor Dipane Hlalele (Chair)

/dd

UNIVERSITY OF KWAZULU-NATAL
INYUVESI YAKWAZULU-NATALI

26 July 2022

Paula Hall (871871741)
School Of Man Info Tech & Gov
Pietermaritzburg Campus

Dear P Hall,

Protocol reference number: HSSREC/00003346/2021
Project title: Exploring the effects of Women in Artificial Intelligence Networks (WAINs) on women's careers in artificial intelligence

Approval Notification – Amendment Application

This letter serves to notify you that your application and request for an amendment received on 20 July 2022 has now been approved as follows:

- Addition of final phase (phase 4)

Any alterations to the approved research protocol i.e. Questionnaire/Interview Schedule, Informed Consent Form; Title of the Project, Location of the Study must be reviewed and approved through an 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.

Best wishes for the successful completion of your research protocol.

Yours faithfully

[redacted]

.....
Professor Dipane Hlalele (Chair)

/dd

UNIVERSITY OF KWAZULU-NATAL
INYUVESI YAKWAZULU-NATALI

16 October 2023

Paula Hall (871871741)
School Of Man Info Tech & Gov
Pietermaritzburg Campus

Dear P Hall,

Protocol reference number: HSSREC/00002352/2021
Project title: Exploring the effects of Women in Artificial Intelligence Networks (WAINs) on women's careers in Artificial Intelligence
Degree: **PhD**

Approval Notification – Amendment Application

This letter serves to notify you that your application and request for an amendment received on 12 October 2023 has now been approved as follows:

- Change from article option to thesis format

Any alterations to the approved research protocol i.e. Questionnaire/Interview Schedule, Informed Consent Form; Title of the Project, Location of the Study must be reviewed and approved through an 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.

HSSREC is registered with the South African National Health Research Ethics Council (REC-040414-040).

Best wishes for the successful completion of your research protocol.

Yours faithfully

[redacted]

.....
Professor Dipane Hlalele (Chair)

/dd