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The influence of artificial intelligence (AI) on personalised learning in the workplace

Siphamandla Msimang

Dr. Manessah Alagbaoso

A research report submitted to the Faculty of Commerce, Law and Management, University of the Witwatersrand, in partial fulfilment of the requirements for the degree of Master of Management in the field of Digital Business

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ABSTRACT

This study investigates the influence of Artificial Intelligence (AI) on personalised learning in the workplace, set within the rapidly evolving landscape of digital technology integration in organisational learning strategies and environments. Addressing the gap in literature regarding AI's role in enhancing workplace learning experiences, this research utilises the Technology-Organisation-Environment (TOE) framework and Senge's Learning Organisation theory as its conceptual underpinnings.

Through a quantitative methodology, data was collected from 391 participants across various industries via an AI-powered chatbot survey interface, focusing on employees' engagement in self-directed learning activities, perceptions of AI-enhanced personalised learning, and the factors influencing their engagement in workplace learning.

The study reveals that employees perceive AI as an enhancer of personalised learning experiences in the workplace, with its adoption being significantly influenced by factors such as technological compatibility, organisational support, and a conducive regulatory environment. The findings offer an understanding of the multifaceted nature of AI in enhancing personalised learning experiences in the workplace, providing insights for future strategies and implementations in this evolving field.

The conclusion draws attention to the transformative potential of AI in enhancing personalised learning within the workplace, advocating for its strategic integration to fully leverage its benefits. By aligning AI-driven learning tools with organisational cultures that prioritize continuous learning, organisations can significantly improve employee engagement, skills development, and ultimately, their competitive advantage in the digital era.

KEYWORDS

Artificial Intelligence, Personalised Learning, Workplace Learning, AI-Driven Learning, Self-directed Learning, Organisational Culture, Continuous Learning.

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I am grateful to the 391 participants who generously shared their time and insights, making this research possible. Their engagement was instrumental in exploring the intricacies of AI in personalised workplace learning.

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DECLARATION

I, Siphamandla Msimang, declare that this research report is my own work except as indicated in the references and acknowledgements. It is submitted in partial fulfilment of the requirements for the degree of Master of Management in the field of Digital Business at the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination in this or any other university.

Name: Siphamandla Msimang

Signature:  **Signed** at Parktown, Johannesburg

On the 21 of February 2024

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Abbreviations and Acronyms

AI	Artificial Intelligence
BIA	Business Intelligence and Analytics
BIS	Business Intelligence System
BSA	Boy Scouts of America
ERP	Enterprise Resource Planning
EU	European Union
GDPR	General Data Protection Regulation
HR	Human Resources
ICT	Information and Communication Technology
IOT	Internet of Things
IT	Information Technology
ML	Machine Learning
OLC	Organisational Learning Culture
PGC	Post-Graduate Committee
SME	Small and Medium Enterprise
SPSS	Statistical Programme for Social Sciences
TAM	Technology Acceptance Model
TEI	Technical Education Institutions
TOE	Technology-Organisation-Environment
US	United States
UTAUT	Unified Theory of Acceptance and Use of Technology

Chapter 1: Introduction

1.1 Statement of Purpose

The purpose of this study is to explore the influence of artificial intelligence (AI) on personalised learning within continuous learning organisations.

1.2 Background of the Study

The contemporary workplace has undergone a rapid transformation due to technological disruptions, significantly impacting business practices, employee work methodologies, and societal dynamics globally. The COVID-19 pandemic accelerated this evolution, resulting in widespread adoption of AI, automation, data analytics, and communication tools across various industries. These advancements have not only streamlined operations and increased productivity but also introduced new challenges such as the need for upskilling employees and addressing data privacy concerns. The integration of AI and automation has particularly reshaped job roles, necessitating continuous learning and adaptability among the workforce. According to Panigrahi (2020), these advancements have not only affected businesses but also changed societal norms. Weinstein et al. (2019) highlight AI as a pivotal force with the capacity to redefine the future landscape of employment fundamentally.

Gao and Liu (2023) conducted a study on the application of AI in personalising interactive marketing, emphasising the transformative impact that AI-powered personalisation has had on digital commerce and marketing strategies. This same technology can be applied to workplace learning, tailoring content to individual learning styles, preferences and goals (Bankins & Formosa, 2023). According to Farmiloe (2023), this personalised approach improves the employee experience, leading to increased knowledge retention, skill development and overall satisfaction with learning. A study by Smith (2020) highlights that forward-thinking organisations are strategically addressing employee learning needs, recognising that agility is essential for competitiveness. However, employees face challenges in dedicating time to learning amidst distractions, unless the learning is seamlessly integrated into the organisational fabric (Smith, 2020).

The progression of AI, machine learning (ML) and smart technology is paving the way for personalised training and development. According to Weinstein et al. (2019), real-time insights provided by AI enable managers to optimise employee onboarding, tailor training and support

ongoing development. AI's potential to transform training, improve workforce management and enhance learning experiences is evident. Organisations can use AI to optimise scheduling, increase training effectiveness and provide personalised learning that is aligned with industry trends, fostering a culture of continuous learning for competitiveness. However, ethical considerations and inclusivity must guide the strategic implementation of AI in workplace (Weinstein et al., 2019).

1.3 Research Problem

The impact of digital disruption on the workplace, evolving trends and the need for companies to engage in continuous learning and development for survival and competitiveness mean that employees should acquire the requisite training and development to remain agile and competitive (Budhiraja, 2023; Randall et al., 2022; Wiltshire, 2022). To maintain a competitive edge, organisations require talent management systems that keep employees informed about industry changes (Lin & Huang, 2021; Weinstein et al., 2019). AI-powered personalised learning has the potential to assess training needs and offer tailored skill development aligned with industry advancements, thus enabling employees to stay relevant and benefiting organisations' competitiveness.

Empirical research primarily conducted on a global scale suggests that AI algorithms can predict learning outcomes and deliver personalised materials (Hashim et al., 2022). Scholarly works emphasise the utilisation of AI-driven technologies for adaptive learning, personalised content delivery and individualised instruction (Alam, 2021; Bhutoria, 2022; Vincent-Lancrin & van der Vlies, 2020). When combined with educational technology, AI enhances teaching methods, tracks progress and improves the learning experience (Hashim et al., 2022). However, an initial literature review by the current study identifies gaps, with literature primarily focusing on AI personalised learning in the education sector. This points to the need for consideration of the adoption of AI learning within the workplace environment. Organisations that embrace technology tend to survive longer, which suggests that AI applications for upskilling and informing staff about evolving technologies are crucial for survival and competitive advantage. Thus, the establishment of a lifelong learning culture, such as is commonly found in continuous learning organisations, becomes essential.

1.4 Research Objectives

Derived from the research problem stated above, three research objectives are formulated:

RO1: Investigate the influence of AI to improve personalised learning and development in the workplace.

RO2: Investigate the importance of a continuous learning organisational work environment for personalised AI-driven learning adoption.

RO3: Investigate key influential factors affecting personalised AI-driven learning within the work environment.

1.5 Rationale

The importance of this study lies in the increasing challenges that organisations face in attracting, training, managing and retaining talent in today's agile digital world (Weinstein et al., 2019). As organisations navigate the complexities of digital transformation, they face challenges such as rapidly evolving skill requirements, employee resistance to change, and the need for continuous upskilling. AI-driven personalised learning offers a solution by providing tailored learning experiences that can quickly adapt to these changes. This study also aims to build on the body of knowledge in exploring the role of continuous learning in organisations and the need for innovative enterprise workforce-management solutions (Weinstein et al., 2019), to enhance employee engagement, satisfaction and retention. This body of knowledge emphasises the need for organisations to prioritise employees' professional development (Budhiraja, 2023; Smith, 2020; Wiltshire, 2022).

The value of this research study lies in its exploration of the use of AI, ML and the internet of things (IoT)/smart technology to streamline personalised training and development programmes. It assesses the effectiveness of using this technology to make informed staffing decisions based on real-time analytics for assessing employees' training needs and providing tailored recommendations of relevant developmental skills aligned with the latest industry advancements (Baek-Kyoo & McLean, 2019; Lin & Huang, 2021; Weinstein et al., 2019). Providing training that is tailored to employee needs aims to ensure that employees maintain relevance within their respective job sectors and improves their learning experience through personalised assistance (Pillai et al., 2023; Place, 2020). Overall, this study addresses the importance and potential contributions of research related to talent organisational learning, continuous learning, AI and personalised learning.

1.6 Delimitations of the Study

The following delimitations define the boundaries of the study, indicating the aspects that are intentionally excluded or not within the scope of this research.

- The study excludes a discussion of attracting, training, managing and retaining talent, as well as employee scheduling and retention, as these topics are beyond the scope of the research.
- The study does not explore the impact of the organisational learning culture (OLC) on job satisfaction, turnover intentions and job performance during organisational change.
- The study does not focus on the specific strategies or practices used to convey the value of continuous learning, flexibility, and creativity by leaders and managers.
- The study does not delve into the detailed recommendations for fostering strategic change through organisation learning and continuous improvement.

1.7 Definition of Terms

Continuous Learning:	The ongoing process of acquiring new knowledge, skills and competencies within an organisation (Billett, 2000).
Personalised Learning:	Involves tailoring learning experiences, content and approaches to meet the specific needs, preferences and goals of individual learners (Shemshack & Spector, 2020).
Artificial Intelligence (AI):	The simulation of human intelligence in machines that can analyse data, learn from patterns, and make autonomous decisions or recommendations (Seo et al., 2021).
Machine Learning (ML):	A subset of AI that enables systems to automatically learn and improve from experience without explicit programming (Sarker, 2021).
Continuous Learning Organisation:	An organisation that promotes and facilitates ongoing learning and development opportunities for its employees, enabling them to acquire new skills and knowledge continuously (Sanz-Valle et al., 2011).
AI-Driven Learning:	The use of AI to enhance the learning experience, offering personalised instruction, real-time feedback and resource recommendations that are based on data analytics (Seo et al., 2021).
Self-Directed Learning:	A process of learning where individuals proactively identify their learning requirements, set objectives for their education, discover resources for learning, choose and apply strategies for learning, and assess the results

	of their education, either independently or with assistance from others. (du Toit-Brits, 2019).
Adaptive Learning:	A dynamic approach to education that utilises AI algorithms to tailor learning content and experiences, based on individual learners' progress, strengths, weaknesses and preferences (Martin et al., 2020).
Regulatory Support:	The framework of laws, regulations and policies that govern the development, implementation and use of technology, including AI, within specific industries or sectors and provide guidelines that can facilitate or hinder technological adoption (Depietro et al., 1990).
Systems Thinking:	A holistic approach to analysis that focuses on the way that a system's constituent parts interrelate and how systems work over time and within the context of larger systems (Depietro et al., 1990).

1.8 Assumptions

The overall assumption of this study is that the use of AI is essential for streamlined and personalised training and development in organisations. The study also assumes that AI has the potential to transform talent-management practices to enable organisations to become progressive. Further assumptions of this study are:

- AI enables the evaluation and analysis of employee data, enabling an automated evaluation and proposal of customised training programmes. It also allows for the prediction of training and scheduling requirements, making use of variables such as sales projections, analysis of foot traffic and seasonal trends.
- AI equips managers with an immediate understanding of their workforce, supporting processes such as employee induction, tailored training programmes and continuous professional development. Additionally, AI and analytics can also help human resource (HR) professionals make data-driven decisions that benefit administration and improve employee experience.
- The implementation of AI in training and workforce management can improve workflow, streamline operations, and improve employee engagement and satisfaction. It can also lead to higher accuracy and efficiency and improve decision-making capabilities.
- Employees value continuous learning and professional development, and organisations should invest in employees' professional growth to increase engagement, satisfaction and retention.

1.9 Chapter Outline

Below is a chapter outline for the research report, with summaries for each chapter from 1 to 6. Each subsequent chapter builds upon the foundation in chapter 1, with chapter 2 providing a review of the literature to situate the research within the broader academic discourse. Chapter 3 details the methodology, explaining the research design and data collection strategies that ensure rigor and reliability. Chapter 4 presents the results, offering empirical evidence to address the research questions. Chapter 5 discusses these findings in relation to existing theories and literature, highlighting their implications. Finally, chapter 6 concludes with a summary of key insights, practical recommendations, and suggestions for future research, thus providing a comprehensive understanding of AI's influence on personalised learning in the workplace.

Chapter 1: Introduction

This chapter sets the stage for the research report by outlining the context, significance, and objectives of the study. It begins with a statement of purpose, explaining the investigation into how artificial intelligence (AI) could influence personalised learning in the workplace. The background provides an overview of the evolving workplace dynamics, the role of AI in enhancing learning and development, and the shift towards personalised learning approaches. Research objectives are clearly defined, aiming to explore AI's impact on personalised learning, the importance of a continuous learning organisational culture, and key factors affecting personalised AI-driven learning. The rationale behind the study is discussed, highlighting the need for innovative solutions in talent management and learning amidst digital transformation. Delimitations, definitions of terms, and assumptions provide clarity on the scope, conceptual boundaries, and foundational premises of the research.

Chapter 2: Literature Review and Theoretical Framework

This chapter offers an examination of existing scholarly work and theoretical underpinnings relevant to the study. It reviews literature on AI's role in personalised learning, organisational learning, and the integration of AI in workplace learning. The theoretical framework introduces the Technology-Organisation-Environment (TOE) model and Senge's Learning Organisation theory as lenses through which the research objectives are explored. The discussion extends to technological factors such as relative advantage and compatibility, organisational dimensions like personal mastery and team learning, and environmental aspects including regulatory support and competitive pressure.

Chapter 3: Research Methodology

The methodology chapter describes the quantitative research approach adopted to investigate the study's objectives. It details the research design, including the use of an AI-powered chatbot survey interface for data collection. The chapter outlines the process from the development of the survey instrument, based on existing literature and theoretical frameworks, to the selection of a purposive sample of employees from various organisations. Data analysis strategies are explained, emphasising the use of descriptive statistics and multiple linear regression analysis to test the formulated hypotheses.

Chapter 4: Presentation of Results

This chapter presents the findings from the data collected through the survey. It provides descriptive statistics on participants' demographics, their perceptions of AI in workplace learning, engagement in self-directed learning, and the extent of AI implementation. The results of regression analyses testing the hypotheses are detailed, offering insights into the factors influencing AI-driven personalised learning in the workplace.

Chapter 5: Discussion

The discussion chapter interprets the results in the context of existing literature, providing a comprehensive analysis of the findings. It explores the implications of AI's influence on personalised learning in the workplace, engaging with counterarguments and offering reflective insights. The discussion integrates the results with the theoretical frameworks and literature reviewed in Chapter 2, elucidating the significance of technological, organisational, and environmental factors in the adoption and effectiveness of AI-driven learning solutions.

Chapter 6: Conclusion and Recommendations

The final chapter concludes the research by summarising key findings, contributions, and limitations of the study. It reflects on the research objectives and the extent to which they were met, highlighting the practical implications for organisations seeking to leverage AI for personalised learning. Recommendations for future research and practice are provided, suggesting areas for further exploration and strategies to enhance the implementation of AI in learning and development initiatives.

Chapter 2: Literature Review and Theoretical Framework

2.1 Introduction

This chapter reviews the literature on the influence of AI on personalised learning in the workplace as a background to the study. Thereafter, it reviews a theoretical framework and theory that are relevant to the study and proposes a conceptual framework for use in the study to investigate AI influence on personalised learning for workplace adoption.

The literature review mind map developed for this study is presented in Figure 1. As shown in Figure 1, organisational learning and AI are positioned as the foundational pillars of this research. Within the context of organisational learning, the investigation delves into continuous learning in the workplace. Workplace continuous learning necessitates the provision of personalised learning and development for individuals, which ultimately becomes the central focus of this research. Additionally, the exploration encompasses the various applications of AI in organisational learning, subsequently linking back to the primary research objective (which is to investigate the influence of AI to improve personalised learning and development in the workplace), as shown in Figure 1.

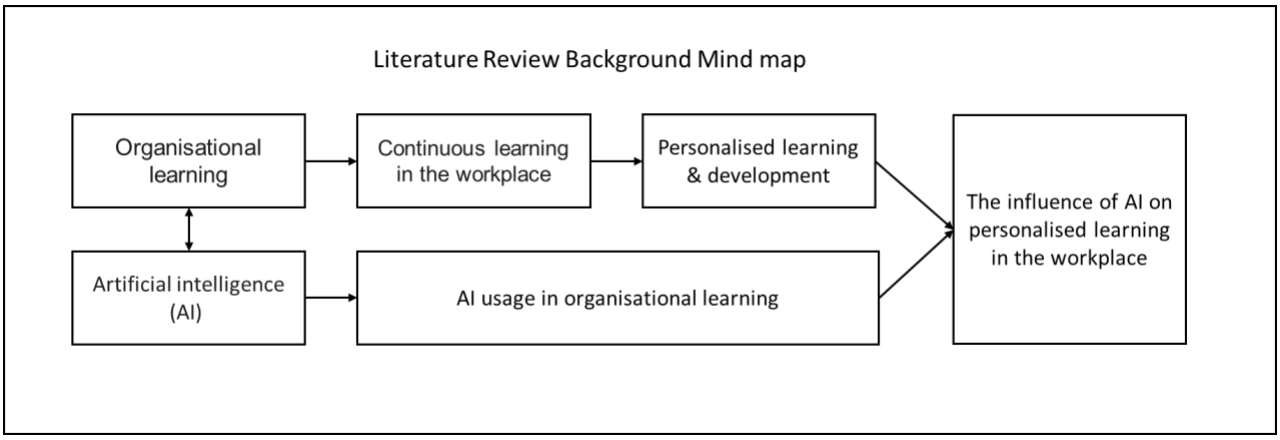

Figure 1: Literature Review Mind Map

2.2 Background to the Study

To provide a background to this study, the literature review follows the path shown in Figure 1, starting with an AI perspective. This approach is crucial as it sets the stage for understanding the technological advancements that drive personalised learning.

2.2.1 Artificial intelligence

The integration of evolving technology such as AI into workplaces is growing, as indicated by Bader and Kaiser (2019). Often termed cognitive systems or ML algorithms, AI can automate data analysis and decision-making without human intervention, although concerns about control loss and unintended consequences can arise (Bader & Kaiser, 2019). According to Wilkens (2020), the benefits and challenges of AI and ML in organisational contexts have been explored, with the finding that AI/ML can improve individual and organisational learning through the provision of accurate information, although potential unintended effects also exist. For effective workplace AI integration, continuous learning and professional development are crucial. A study by Billiot (2023) highlights that employees must not only acquire new knowledge but also adapt to technological advancements. The adoption of frameworks such as Fink's Taxonomy of Significant Learning, which is a wholistic model of learning experiences that encourages educators to design courses that go beyond mere content delivery, promoting deep engagement and lasting understanding. This can facilitate employees' engagement in ongoing learning processes and bolster their development in the context of AI (Billiot, 2023).

2.2.1.1 Artificial intelligence usage in organisational learning

AI has a substantial impact on organisational learning and performance, offering potential benefits in various aspects of learning. Kitsios and Kamariotou (2021) assert that AI acts as a crucial instrument in augmenting business value through task automation, stakeholder engagement, and the facilitation of new product and service development. The incorporation of AI into organisational learning involves varied decision-making processes (Shrestha et al., 2019). Furthermore, Gonzalez et al. (2019) emphasise the importance of research and collaborative efforts in assessing the impact of AI on talent management.

According to Jarrahi et al. (2023), the role of humans in contextualising AI-generated knowledge and their collaboration with AI systems for mutual learning is crucial for organisational learning. The role of human intervention is contextualised in a study by Kim et al. (2022) which discusses the impact of AI systems on learner–instructor interaction in online learning. The study underscores the importance of human involvement in managing and contextualising the knowledge generated by AI systems (Kim et al., 2022). AI's potential lies in its self-learning capacity, fostering competitive advantage in knowledge-intensive contexts (Jarrahi et al., 2023). Overall, AI's impact on organisational learning is multifaceted, ranging from enhancing performance to reshaping talent management and fostering collaborative learning paradigms.

2.2.2 Organisational learning

Organisational learning, which is closely linked to the concept of a learning organisation, emphasises continuous improvement, innovation and the integration of collective knowledge. Research by Sanz-Valle et al. (2011) highlights this relationship between organisational learning and continuous improvement, while Pham and Hoang (2019) show that organisational learning capability positively affects business performance, especially in dimensions such as management commitment and knowledge integration. Organisational culture, transformational leadership and structure are crucial determinants of effective organisational learning and innovation (Sanz-Valle et al., 2011). Successful organisational learning, as noted by Pudjiarti and Priagung Hutomo (2020), leads to behaviour changes, improved performance and competitive advantage through innovation.

2.2.2.1 Continuous learning in the workplace

Continuous learning within the workplace, as emphasised by Billett (2000), plays a critical role in employee development and organisational growth. This involves employees' ongoing acquisition of knowledge, skills and competencies through diverse learning activities. Budhiraja's study (2021) delves deeper into this concept, investigating the relationship between continuous learning, contextual performance in a post-merger Indian organisation, and change-efficacy, which is defined as an individual's belief in their ability to effectively adapt to changes. The research reveals that continuous learning positively influences employees' change-efficacy, which in turn mediates the link between continuous learning and contextual performance. This underscores how continuous learning enhances employees' adaptability to change and overall effectiveness in their roles.

Recognising the integration of learning and work, as highlighted by Park et al. (2021), the workplace becomes a pivotal avenue for boosting employee competence and performance. Continuous learning in this context plays a pivotal role in fostering employee development; cultivating positive work attitudes, job satisfaction and engagement; and ultimately contributing to enhanced organisational success and productivity.

2.2.2.2 Personalised learning

Personalised learning, as explored by Makhambetova et al. (2021), is an education approach that shapes instruction to meet individual learners' needs, interests and strengths. This method recognises diverse learning styles and aims to provide personalised support. Shemshack and

Spector (2020) highlight that personalised learning enhances individuals' knowledge and skills by enabling them to learn at their own pace. Technology, such as AI-based platforms, plays a crucial role in enabling this approach, as noted by Harry (2023). Implementing personalised learning requires shifting instructional practices to create supportive online environments that empower learners to take charge of their education, as highlighted by Basham et al. (2016). In essence, personalised learning optimises education by catering to individual learners' unique requirements.

2.2.3 The influence of artificial intelligence on personalised learning in the workplace

AI is poised to transform personalised workplace learning significantly, offering advantages such as personalised development, customised instruction and enhanced efficiency through automation (Poquet & Laat, 2021; Seo et al., 2021). AI-driven tools can create engaging and interactive learning environments by integrating adaptive learning algorithms that tailor educational content to individual needs. For example, AI-powered learning management systems can analyse employee performance data to provide customised training modules, ensuring that each learner receives the most relevant and effective instruction. Additionally, automation of routine tasks enables employees to focus on more complex and value-added activities, enhancing overall productivity. Case studies, such as the implementation of AI-driven onboarding programs at large corporations, demonstrate how personalised learning facilitated by AI can lead to faster skill acquisition, higher engagement levels, and improved job performance (Poquet & Laat, 2021). Furthermore, AI systems enhance online learning experiences by providing personalised interactions creating a more engaging, effective, and supportive learning environment tailored to each student. This personalisation not only enhances the learning experience but also fosters better academic outcomes and greater student satisfaction. However, this necessitates the formulation of meticulous guidelines to safeguard users, primarily due to concerns surrounding data protection, user security, ethical considerations, and the quality of AI-human interactions (Seo et al., 2021). The importance of AI in generating personalised profiles for learners is highlighted by Hashim et al. (2022). Nevertheless, there is a prevailing concern that AI’s emphasis on knowledge acquisition could potentially constrain learner autonomy (Poquet & Laat, 2021). Adopting a capability perspective of lifelong learning could empower individuals in career-related discussions (Poquet & Laat, 2021). Furthermore, the synergistic application of AI with workplace learning analytics is identified as a potent enhancer of professional growth and decision-making processes (Poquet & Laat, 2021).

2.3 Theoretical Framework

In order to explore the research objectives and the influence of AI on personalised learning in the workspace, the Technology-Organisation-Environment (TOE) framework (Depietro et al., 1990) and Senge's Learning Organisation theory (Senge, 2006) were applied. These frameworks provide valuable insights into the factors that shape the acceptance and implementation of AI in personalised learning and were chosen for their relevance to organisational learning and AI, the foundational pillars of this study.

This research study adopted the TOE model introduced by Depietro et al. (1990) as a theoretical framework for investigating the strategic decisions made by firms regarding the adoption of innovations. The TOE framework has gained recognition for its holistic evaluation of the multifaceted determinants of adoption. While alternative frameworks such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) were considered for this study, these theoretical frameworks are frequently critiqued for their pragmatic and technology-centric forecasts, which place technology, rather than users and firms, in the driver's seat of adoption (Chittipaka et al., 2023). Additionally, the TOE framework has been acknowledged for its efficacy in examining value creation and innovation acceptance, offering superior insights into the internal and external dynamics of firms (Chittipaka et al., 2023). The TOE framework's applicability extends to various contexts, including the adoption of mobile reservation systems by hotels (Wang et al., 2016), remote work (Ng et al., 2022), cloud computing (Aligarh et al., 2023) and the implementation of smart manufacturing systems (Shukla & Shankar, 2022). This range of contexts underscores the potential usefulness of the TOE framework in comprehensively investigating the impact of AI on personalised learning within work environments.

Within the organisational dimension of the TOE framework, this study delves into the dimension of organisational learning by drawing upon Senge's Five Disciplines of a Learning Organisation (Senge, 2006). Senge's (2006) framework encapsulates a series of principles and practices designed to cultivate continual learning and development within organisations (Bui & Baruch, 2010). The Five Disciplines of a Learning Organisation, as conceptualised by Peter Senge (2006), have been the subject of extensive scholarly examination in research literature. Bui and Baruch (2010) provide a systemic perspective of the establishment of learning organisations that is grounded in Senge's five disciplines. These authors emphasised the significance of individual learning as a precursor to personal mastery, a pivotal discipline for the existence of a learning

organisation. In the context of the current study, which concerns the impact of AI on personalised learning, Senge's (2006) theory offers guidance to organisations in fostering a culture of learning that embraces AI technologies for personalised learning. Furthermore, the theory underscores the necessity of systems thinking, mental models, shared vision, and team learning to integrate AI into the learning process effectually (Bui & Baruch, 2010).

The three dimensions of the TOE model are elaborated on below, with Senge's (2006) theory discussed under the organisational dimension.

2.3.1 Technology dimension

The technology dimension aligns with the first research objective for this study, which is to investigate the influence of AI to improve personalised learning and development in the workplace. The technology dimension of the TOE framework assumes a central role in shaping firms' adoption decisions regarding innovative technologies: in the context of this study, the adoption of AI in personalised learning. According to Depietro et al. (1990), this dimension encompasses the firm's technological preparedness, which collectively influences the firm's inclination towards adoption. It encompasses factors such as the relative advantage, compatibility, and complexity of both internal and external technologies (Chittipaka et al., 2023). Additionally, this dimension encompasses the extent to which technology has been integrated within the organisation, which reflects the firm's receptiveness to technological advancements that are aligned with its specific requirements (Wallace et al., 2021).

This research on AI technology in personalised learning focuses on two technological factors: relative advantage and compatibility. These factors are analysed to assess the benefits of AI personalised learning over traditional learning methods and AI technology enabling personalised learning.

2.3.1.1 Relative advantage

According to Rogers et al. (2014), the term "relative advantage" refers to the extent to which an innovation is perceived as superior to the existing concept that it replaces. A study by Nam et al. (2021) notes that, if the innovation is deemed to provide operational and strategic value that outweighs established practices and processes, its merits will have a positive impact on its adoption. This is particularly relevant in the context of AI and robotics, which are recognised for delivering various advantageous outcomes, spanning strategic incentives to operational

efficiencies (Nam et al., 2021). Similarly, Stenberg and Nilsson (2020) found that the notion of relative advantage appears to have a strong influence on AI adoption. Within the scope of this research, relative advantage pertains to the extent to which AI applications in personalised learning are perceived as superior to competing technologies that do not utilise self-learning methodologies.

In the study by Nam et al. (2021), participants identified key AI advantages as cost reduction, revenue generation and enhanced customer experience. AI improved operational efficiency, which had the effect of reducing costs, as exemplified by electricity backup and sustainability systems. Revenue benefits arose from analytics-driven marketing, and customer experience improved with customised services (Nam et al., 2021). Stenberg and Nilsson (2020) highlight the importance of the tech-context of an organisation in an AI readiness assessment, so that AI is aligned with organisational needs. Kruse et al. (2019) note AI's transformative impact on finance, as it reshapes capabilities. Gupta et al. (2022) emphasise the presentation of AI benefits for its adoption, with Tongsuksai et al. (2023) favouring internet-enabled, scalable cloud enterprise resource planning (ERP) systems, hinging on their relative advantage. Chen et al. (2021) link AI adoption to recognising its advantages in terms of customer service, productivity and resource optimisation. These studies underscore the advantage gained for organisations by leveraging AI's merits for its successful implementation. The potential benefits of AI personalised learning over traditional learning methods are now explored below.

Benefits of artificial intelligence over traditional learning methods for personalised learning

Technology’s influence on education and workplace learning is exemplified by the concept of adaptive learning. Hashim et al. (2022) emphasise that AI algorithms can predict learning outcomes and adapt materials to each learner’s goals and previous performance. This capability is a significant relative advantage as it enables the delivery of personalised instruction, accommodating the learning pace and preferences of individuals. According to Vincent-Lancrin and van der Vlies (2020), a prominent example is the Teach to One maths programme in the United States (US), which employs AI to assess students’ skill levels and to deliver appropriate content through various instructional modes.

Similarly, in the workplace, AI-driven communication tools, such as chatbots, have offered a seamless experience for employees, contributing to a positive relative advantage. Pillai et al.

(2023) highlight examples such as Infreedo's AI chatbot "Amber" and "Feedyou" virtual assistant, which enhance employee engagement, address HR-related queries and provide emotional support. These AI chatbots not only streamline HR functions but also elevate the overall employee experience by offering personalised and real-time assistance.

In the area of healthcare, AI's potential to personalise learning and enhance decision-making is also evident. Research has shown that AI's ability to process vast amounts of medical data empowers clinicians with real-time, informed insights, which contribute to improved patient care (Jain et al., 2021). Accordingly, de Laat et al. (2020) highlight that the fusion of AI and personalised learning in the workplace has the potential to reshape professional development and training paradigms. This is because the AI-enabled real-time feedback offers instant, data-driven guidance, which reduces reliance on human instructors and coaches. This not only supports continuous learning but also cultivates self-motivation and reflection, as learners receive timely and pertinent insights.

The importance of technology's impact on learning is further accentuated by its collection and analysis of data. Poquet and Laat (2021) assert that technology's ability to collect data on human behaviour provides insights into improving learning design, feedback and resource recommendations. This ability is exemplified by platforms such as BYJU'S-The Learning App, which combines AI with assessment data to offer personalised learning paths and content recommendations (Vincent-Lancrin & van der Vlies, 2020). This personalised feedback loop enhances the learning experience and constitutes a relative advantage over static, one-size-fits-all approaches.

While the advantages of technology-driven personalised learning are evident, challenges do persist. Alam (2021) highlights the need for proper teacher training and warns of potential privacy concerns related to data collection. Moreover, Shemshack and Spector (2020) point to the evolving nature of personalised learning brought about by rapid technological advancements. This dynamic environment necessitates continuous research and collaboration to maximise AI's potential in education and the workplace.

Lastly, the relative advantage of technology for AI-personalised learning is not confined to traditional educational settings. The integration of AI-powered learning has the potential to impact societal and economic settings as well. For instance, Vincent-Lancrin and van der Vlies (2020)

suggest that AI's role in achieving global educational targets, as outlined in Sustainable Development Goal 4, can invigorate inclusive growth, sustainable development and well-being. This potential societal impact further underscores the importance of leveraging technology for personalised learning.

2.3.1.2 Compatibility

According to Rogers et al. (2014), the term "compatibility" refers to the extent to which an innovation aligns with an organisation's existing values, cultural norms, experiences and user needs. The compatibility factor underscores the need for technology to integrate with an organisation's current processes and consider intangible factors such as values and norms (Rogers et al., 2014). To assess an organisation's compatibility, the new technology should address a specific problem (Stenberg & Nilsson, 2020).

Studies on compatibility have examined various aspects of technology adoption within different contexts. Nam et al. (2021) delved into the challenges facing AI adoption in hotels, highlighting information technology (IT) departments' struggles with outdated technology and limited guest interaction. The adoption of Cloud ERP, as explored by Tongsuksai et al. (2023), was underscored as contingent on its compatibility with existing systems, which could potentially impede integration and lengthen adoption processes. Hradecky et al. (2022) shed light on the cautious approach to AI adoption in the business events industry, where uncertainty about applications and benefits prevails. Interestingly, Srivastava et al. (2022) study on India's Industry 4.0 technology adoption revealed counterintuitive results, where factors such as compatibility and perceived relative advantage were not significant, possibly attributable to the nation's robust IT presence. In sum, these studies collectively contribute to our understanding of the multifaceted dynamics that influence technology-adoption decisions.

Compatibility factor in artificial intelligence-personalised learning for the workplace

The research surrounding AI's integration into personalised learning emphasises the critical role of compatibility between technological advancements and pedagogical methods (Hashim et al., 2022). The intersection of AI with education is marked by the fusion of teaching and learning processes, which ultimately fosters adaptive learning, teacher assessment and virtual classrooms (Hashim et al., 2022). The term "compatibility" in this context refers to the seamless alignment of technology with educational principles. This theme of compatibility gains further significance in the domain of lifelong learning policies, where the omnipresence of technology has triggered

significant transformations across various facets of education and beyond (Poquet & Laat, 2021). This influence is felt not only in formal education but also within workplaces and online learning communities, resulting in a reconfiguration of learning dynamics and individual identities (Poquet & Laat, 2021). The amalgamation of technology-derived data and insights from learning analytics presents opportunities for refining learning strategies, improving feedback loops and offering personalised resource recommendations (Poquet & Laat, 2021). Makhambetova et al. (2021) assert that achieving personalised learning, which hinges on tailoring educational experiences to learners' unique traits and aspirations, necessitates a harmonious integration of AI technology within existing organisational frameworks.

In a different context, Jain et al. (2021) explored the compatibility between AI systems and the core values of the medical field. According to these authors, the potential of AI to provide real-time data-driven insights points to the need for aligning these capabilities with the deeply ingrained reliance on human clinical judgement. The compatibility factor here extends beyond technical integration to encompass the harmonisation of AI's functionalities with the ethical values that are intrinsic to healthcare. As the landscape of AI-driven technologies continues to evolve, the importance of compatibility increases, particularly within the realm of lifelong learning (Poquet & Laat, 2021). The advent of AI ushers in both favourable and unfavourable consequences for cognitive and developmental processes. A nuanced engagement with intelligent tools is thus needed to harness their potential effectively (Poquet & Laat, 2021).

The unfolding potential of AI heralds the rise of adaptive learning opportunities. Cloud-based systems, automated feedback mechanisms and AI-assisted collaborative problem-solving provide glimpses of future educational practices (de Laat et al., 2020). The compatibility of these innovations with existing learning paradigms and organisational structures will play an important role in determining their success. This compatibility will also involve navigating the balance between AI and human involvement. The learner-instructor interaction plays a central role in online education (Seo et al., 2021). Despite AI's provision of tailored support, concerns have arisen regarding the potential homogenisation of the learning experience. Learners' apprehensions about losing avenues for exploration underscore the need for aligning AI's role with learners' agency and educators' expertise. This compatibility necessitates a conceptualisation of AI as a supplementary tool that enriches human intelligence and learning instead of replacing it (Tapalova & Zhiyenbayeva, 2022).

2.3.2 Organisational dimension

This section delves into the organisational dimension of the TOE framework through the lens of Senge's Five Disciplines of a Learning Organisation (Senge, 2006). This dimension correlates with the second research objective for this study, which is to investigate the importance of a continuous learning organisational work environment for personalised AI-driven learning adoption. A personalised learning system can be described as a self-driven arrangement in which an array of adaptive learning instruments is at the disposal of learners to tailor to their individual personal preferences and skills (Bhutoria, 2022). Despite this profusion of resources, however, the assurance of a "motivation to learn" is not guaranteed by this system. This is where the role of the instructors or HR as motivators becomes relevant, assuming a form of motivation that is distinct from the conventional approach, yet even more important in this new system (Bhutoria, 2022). Consequently, an environment that fosters and promotes continuous learning becomes vitally important.

Senge's Five Disciplines of a Learning Organisation

According to Al-Dhuwaihi et al. (2020), the notion of a learning organisation has progressively evolved, with the aim of sharing knowledge and enhancing the efficiency of organisational operations. These efforts have played a pivotal role in shaping the concept of fostering ongoing learning and in creating effective managerial approaches within organisational settings (Al-Dhuwaihi et al., 2020).

A research study conducted by Hutasuhut et al. (2021) observed a growing recognition among organisations regarding the significance of bolstering their employees' capacity for learning. This recognition extends to the development of fresh cognitive frameworks that facilitate the continuous advancement of improvements, innovations and the adept management of uncertain situations (Hutasuhut et al., 2021).

Senge's work, particularly his 2006 book *The Fifth Discipline*, has been instrumental in enabling people to understand learning organisations. Senge defines learning organisations as entities where people continually expand their capacity to achieve desired outcomes, nurture expansive thinking patterns, encourage collective aspirations and promote shared learning (Senge, 2006). Such organisations prioritise personal mastery, mental models, shared vision, team learning and systems thinking to create a culture of continuous learning and improvement (Hutasuhut et al., 2021). These factors play a crucial role in enabling and understanding learning organisations that

aim to embrace AI-driven personalised learning in their operational work environment, given their impetus towards continuous learning and improvement. Senge's (2006) factors of personal mastery, mental models, shared vision, team learning and systems thinking are elaborated on below.

2.3.2.1 Personal mastery

Personal mastery is a foundational discipline that points to the importance of individual growth and development (Senge, 2006). It goes beyond acquiring specific skills; rather, it suggests a lifelong commitment to continuous learning and self-improvement. This discipline encourages individuals within a learning organisation to actively seek opportunities for capacity expansion, motivating them to excel in their respective fields (Hutasuhut et al., 2021). Al-Dhuwaihi et al. (2020) study reinforces this notion by illustrating how personal mastery in educational institutions can result in high levels of personal mastery among the staff of these institutions, aided by training courses and integrated technical systems.

The idea of the self-directed learning approach is supported by NG's (2020) findings, which show that a conducive workplace environment encourages employees to take learning initiatives, which in turn fosters a culture of self-autonomy. NG (2020) examined the successful integration of E-learning in Hong Kong's higher education sector, which was prompted by rapid technological advancements. NG's study underscores the importance of striking a balance between technology integration and cultivating a learning culture. It emphasises the importance of individual learning within learning organisations, which are driven by people. While leaders cannot mandate personal growth, they can stimulate it by creating a nurturing environment and showcasing personal mastery (NG, 2020).

Hutasuhut et al. (2021) contribute to the discourse by illustrating how personal mastery drives self-directed learning. Participants in their study recognised the importance of a conducive workplace for initiating learning initiatives and managing their own learning. This sense of control over development and the focus on proficiency levels were notable. Further studies by Hoe (2019) emphasise the importance of addressing digital competency gaps at all levels and suggest institutionalising personal mastery of digital skills through structured training. In addition, a study by Marik (2022) investigated the concept of personal mastery within a Scouting context. The study revealed that the diverse motivations for pursuing self-development through programmes such as the Boy Scouts of America (BSA) Wood Badge leadership programme point to the importance

of personal mastery, learning culture and leadership support in driving individual growth and institutional development.

2.3.2.2 Mental models

Mental models represent the deeply ingrained assumptions and beliefs that shape an individual's perspective and decision-making process (Senge, 2006). Senge (2006) suggests that bringing these assumptions to light promotes open dialogue and encourages learning through reflection. Hutasuhut et al. (2021) emphasise that mental models are interconnected with personal mastery; as individuals refine their thinking and minimise biases, they become better equipped to adapt in dynamic and uncertain situations.

Marik's (2022) study further underscores the significance of mental models, showing how individuals can reshape their assumptions to foster personal growth and development. In the study, the Wood Badge participants demonstrated this evolution of stereotypes through their reflective practices. This suggests that they were able to challenge and potentially abandon previously held stereotypes, fostering personal growth and development. This aligns with the principles of a learning organisation, which values continuous learning, adaptability, and the evolution of beliefs and practices (Hilden & Tikkamäki, 2013). Hoe (2019) further notes that digital disruptions necessitate challenging existing mental models to devise innovative digital strategies. Transitioning from a techno-centric to a human-centric design approach requires managerial intervention and a shift in paradigm. This transformation was mirrored in the E-learning context discussed by NG (2020), where the E-learning Committee addressed staff resistance by transforming mental models through workshops, which improved E-learning adoption (NG, 2020). Resistance to change, which stems from fear and risk, can be mitigated by fostering a supportive environment and promoting knowledge-sharing among employees (NG, 2020).

2.3.2.3 Shared vision

A shared vision is a collective understanding of an organisation's desired future that aligns individual aspirations with overarching organisational goals (Hutasuhut et al., 2021). A shared vision transcends mere articulation; it compels individuals to internalise the organisational vision as their own, which leads to increased commitment and motivation by these individuals (Senge, 2006). This alignment between personal and organisational visions creates a sense of purpose and direction among the organisation’s members. The research by Al-Dhuwaihi et al. (2020) underscores the importance of a shared vision as a point of reference that guides individuals'

actions and decisions within an organisation. This shared vision serves as a lighthouse, illuminating the path of growth and development for individuals and the organisation as a whole. Hutasuhut et al. (2021) study found that when organisational members have a clear understanding of the organisation's direction and their roles in achieving the vision, they can better align their efforts to realise this vision. This alignment leads to the effective planning, strategising and monitoring of activities, which in turn facilitate the achievement of organisational objectives. In the context of a digital world filled with opportunities and challenges, shared vision takes on even greater significance. Hoe (2019) emphasises that aligning diverse interests and fostering commitment toward a common "big picture" is essential. A shared vision functions as a guide for organisations, bringing together different stakeholders and guiding them towards a desired future state. This role is particularly crucial for management, which should lead and inspire the organisation beyond departmental boundaries. Marik (2022) shows that while not all groups explicitly create shared goals, a shared vision that is centred on common objectives emerges naturally. Diverse experiences influence the range of this vision, even if not all members explicitly share their personal visions. Projects that apply learning immediately after training reinforce this shared vision and enhance the organisation's programme.

Finally, in the realm of change management, shared vision is a catalyst for successful transformation. NG (2020) highlights that effective communication and transparency are crucial for change efforts. Senior management's role in providing information about the vision and development of initiatives is pivotal. Schools focus on employee buy-in and participation, providing resources and strategies for E-learning implementation. The change model involves stages of awareness, desire, knowledge, ability and reinforcement, with shared vision serving as a motivator and guiding force.

2.3.2.4 Team learning

Team learning is a dynamic process through which team members collaborate, share experiences and collectively enhance their capabilities. This discipline recognises that an organisation's capacity to learn is intricately tied to the learning of its constituent teams. Effective team learning fosters an environment of open enquiry, dialogue and shared problem-solving (Senge, 2006). Hutasuhut et al. (2021) assert that teams serve as fundamental units of learning, promoting knowledge exchange and collaborative growth. Marik's (2022) study discusses how team learning in scouting groups encourages the development of leadership skills and a culture of cohesive progress.

Al-Dhuwaihi et al. (2020) study echoes this sentiment by showcasing the effectiveness of group learning, attributed to administrators' efforts in facilitating staff exchanges, improving teaching techniques and promoting positive relationships. Marik's (2022) study on Wood Badge participants underscores the development of teams' collaborative capabilities through insightful thinking and innovative actions. The study highlights how shared goals, constructive dialogue, and addressing challenges contribute to productive teamwork. These elements align with Tuckman's model which describes stages of group development (Jones, 2019), as they represent key aspects of the stages of team development. Shared goals are crucial in the forming stage, constructive dialogue is essential for resolving conflicts in the storming stage, and addressing challenges is a critical part of the norming and performing stages. NG (2020) discusses how team members disseminate learning strategies across teams. Monthly newsletters, awards, videos, workshops and a learning community all foster a collaborative environment that boosts creativity and teamwork. This collaborative approach harnesses collective intelligence to address complex issues. The studies collectively underscore the pivotal role of team learning in promoting self-directed learning, collaborative growth and innovative problem-solving within organisations.

2.3.2.5 Systems thinking

Systems thinking is the discipline that enables individuals to understand and analyse the interdependencies of components within an organisation (Senge, 2006). It offers a holistic perspective that transcends simple cause-and-effect relationships, enabling individuals to see the bigger picture. Hutasuhut et al. (2021) emphasise that systems thinking equips employees with the ability to anticipate consequences and make informed decisions in complex and dynamic scenarios.

Recent research has focused on systems thinking in a range of organisational contexts. Hutasuhut et al. (2021) study findings revealed that over half of the study participants (53.3%) demonstrated an ability to perceive themselves as integral to a larger system, where their actions would influence the broader context. These participants actively sought connections with others, aiming to enhance their contributions while aiding colleagues. Hoe's (2019) study found that the practice of systems thinking enabled employees to comprehend their roles within the organisation and the repercussions of their actions, which led to increased self-directed learning.

Within the digital landscape, the importance of diverse teams has pointed to the "silo mindset" as a hindrance to innovation, underlining the necessity of internal collaboration for successful digital

solutions. Hoe (2019) further stresses the need for agile teams that can adapt swiftly to market changes. A collaborative environment must be cultivated by management to enable effective learning and teamwork. Marik's (2022) research on Scouts BSA highlights the application of systems thinking, where disciplines and processes form a cohesive system. The use of a universal language facilitates communication, while Wood Badge's unique approach, combining instruction, demonstration and practice, enhances leadership skills. This distinctive methodology positively influences participants' perceptions of Scouts BSA, highlighting its value in fostering effective leadership within a complex system. These studies collectively underscore the importance of systems thinking, teamwork and interconnectivity in enhancing organisational efficiency and fostering self-directed learning.

2.3.2.6 How Senge's five disciplines relate to organisational learning

Fostering a culture of learning

Collectively, the studies shed light on how Senge's five disciplines contribute to the cultivation of a culture of learning within organisations. Personal mastery empowers individuals to take ownership of their growth journey, promoting self-directed learning and skill enhancement (Hutasuhut et al., 2021). Mental models encourage critical reflection and the reshaping of assumptions, which facilitate personal and professional development (Hutasuhut et al., 2021; Marik, 2022). Shared vision aligns individual motivations with organisational goals, fostering commitment and a sense of purpose (NG, 2020). Team learning promotes collaborative growth and knowledge exchange among diverse groups (Hutasuhut et al., 2021; Marik, 2022). Systems thinking equips employees with the ability to navigate complex environments, facilitating effective decision-making (Hoe, 2019; Hutasuhut et al., 2021).

The role of leadership: Catalyst for learning

Leadership emerges as a critical catalyst in nurturing a learning organisation. NG (2020) highlights the role of leaders in transforming mental models, challenging assumptions and promoting a shared vision. Marik's (2022) study underscores the impact of leadership programmes, such as Wood Badge, on fostering a shared vision and team learning. Effective leadership not only show their teams what they should be aiming for but also creates an environment that encourages experimentation, learning and adaptation.

A framework for success in the modern age

Senge's five disciplines offer a comprehensive framework for organisations to use in navigating the challenges and opportunities presented by the modern business landscape. They relate to this study's second research objective: to investigate the importance of a continuous learning organisational work environment for personalised AI-driven learning adoption. Through personal mastery, mental models, shared vision, team learning and systems thinking, a culture of learning, adaptability and innovation can be nurtured. These disciplines, when interwoven with effective leadership, empower organisations not only to survive but also to thrive in dynamic and digital-driven environments. A commitment to growth and continuous improvement is pivotal as organisations continue to evolve, seamlessly integrating these disciplines into their fabric for enduring success.

2.3.3 Environmental dimension

The environmental dimension aligns with the third research objective for this study, which is: to investigate key influential factors affecting personalised AI-driven learning within the work environment.

The environmental dimension of the TOE framework concerns how external factors in the environment impact on the adoption and implementation of technology. Such factors encompass government regulations, market and technology support, industry dynamics, competitors and suppliers (Depietro et al., 1990; Wallace et al., 2021). Research shows that IT decision makers are attuned to these influences and respond accordingly, with some additional factors beyond the TOE framework's scope (Wallace et al., 2021). The environmental dimension entails external parties, such as competitors, suppliers, customers and governments, shaping innovation by determining needs, providing resources and implementing technology (Dewi et al., 2018). Factors such as competitive pressure, partner readiness, socio-cultural considerations, government support and technology infrastructure interact in this dimension (Awa & Ojiabo, 2016). Neumann et al. (2022) add that government regulations and customer expectations, especially in public organisations, exert pressure on technology adoption. The influence of the environmental dimension is evident in the adoption of business intelligence and analytics (BIA), where competitive pressure, market factors, and regulatory compliance impact its level of use, positioning BIA as a strategic tool for organisations (Mohammad et al., 2022). Contrasting findings emerge regarding Industry 4.0 adoption: while Srivastava et al. (2022) found no significant link between the environment dimension and adoption in Technical and Vocational Education Institutions (TEIs) in their study, other research suggests that environmental factors such as

competitive pressure and regulatory support can play a significant role in the adoption of personalised AI. Both of these factors are important in the scope of this study and are further unpacked below.

2.3.3.1 Competitive pressure

Within today's competitive business landscape and the proliferation of emerging technologies and providers, the competitive aspect of the environment is important to consider, particularly in the TOE framework. Competitive pressure, which is characterised by the degree of rivalry prevailing in the market within which an enterprise operates, is a critical determinant of technology adoption (Stjepić et al., 2021). This dimension is underscored by research that shows that small and medium enterprises (SMEs) that aim to fortify their competitive position in a volatile market perceive competition and vendor quality as potential risks to address in Business Intelligence System (BIS) adoption (Stjepić et al., 2021).

The global race for AI supremacy is emblematic of competitive dynamics, with nations such as the US, China and the European Union (EU) pursuing divergent approaches (Stenberg and Nilsson, 2020). Competition is observed to influence technology adoption rates as innovations alter competitive dynamics among firms (Nam et al., 2021). Firms that achieve a competitive edge through new technology adoption often spur on competitors to consider similar adoptions. Empirical studies establish the link between competitive pressure and the intention to adopt technology, demonstrating its pivotal role in fostering an environment that is conducive to innovation (Gupta et al., 2022). This factor resonates across industries, including insurance, talent acquisition and cloud ERP systems, where competitive pressure compels firms to innovate and adopt technology to remain viable in the market (Alam, 2021; Pillai & Sivathanu, 2020; Tongsuksai et al., 2023).

In the context of AI adoption, the influence of competitive pressure varies, with studies revealing complex relationships and potential variations according to industry context (Chen et al., 2021). Nonetheless, it is evident that competition is a driving force that shapes technology adoption, innovation and strategic decision-making within organisations.

2.3.3.2 Regulatory support

In the realm of technology adoption, the regulatory environment looms as a formidable force, as it encompasses legal obligations, policies and government interventions that intersect with

innovations. Within the TOE framework, the regulatory dimension assumes a significant role in shaping AI adoption (Depietro et al., 1990). Compliance with laws that span taxation, patents and other policies, along with the General Data Protection Regulation (GDPR) which is a comprehensive data privacy regulation enacted by the European Union (EU) in 2018, sets the stage for organisations' innovation endeavours (Regulation, 2018). However, these regulations can also pose challenges, such as the potential impact of data anonymisation requirements on AI model training. The dynamic nature of the regulatory landscape is exemplified by the emergence of AI principles in over 35 countries, which reflects a global effort to regulate the burgeoning field (Stenberg & Nilsson, 2020).

The integration of technology requires meticulous consideration of legal facets, including privacy, security and government regulations. For instance, industries such as hospitality grapple with utilising personal data while navigating data privacy laws and ethical considerations, both nationally and internationally (Nam et al., 2021). In governmental contexts, complex interpretations of diverse laws impact AI project initiation, often requiring the involvement of top management and legal departments (Stenberg & Nilsson, 2020). Furthermore, regulatory support emerges as a decisive predictor of behavioural intention in technology adoption, with the insurance sector exemplifying how adhering to proper implementation regulations positively influences AI adoption (Gupta et al., 2022).

AI ethics and data access, identified as cross-contextual influencing factors, introduce a layer of complexity. Ethical considerations permeate the AI landscape, influencing both adoption decisions and broader ethical frameworks. However, in the interviews conducted as part of Neumann et al. (2022) study on the adoption of artificial intelligence in public organisations, discussions around these ethical aspects were notably underrepresented. This observation suggests a need for proactive governance and regulations to uphold public values. Similarly, data access underscores the intricate interplay of technological, organisational and environmental contexts, necessitating a comprehensive approach to explicate the driving forces behind AI adoption (Stenberg & Nilsson, 2020).

In diverse sectors, including exhibitions and financial services, regulatory requirements exert their influence. Event managers wrestle with the privacy implications of facial recognition, emphasising the importance of balancing AI benefits with ethical and privacy concerns (Hradecky et al., 2022). Conversely, the financial domain grapples with extensive regulatory requirements, with resource

allocation often prioritising compliance over digital transformation initiatives such as AI (Kruse et al., 2019). In conclusion, the regulatory environment profoundly shapes technology adoption across industries. From the GDPR to government policies, regulations steer the course of innovation, offering challenges and opportunities that organisations must navigate to harness the potential of emerging technologies such as AI.

Regulations in artificial intelligence personalised learning

Ethical considerations in AI personalised learning encompass algorithmic trust, privacy and data security, which are crucial for building trustworthy AI systems (de Laat et al., 2020). Transparent data governance and standards are pivotal for guiding data access and overcoming research fragmentation (de Laat et al., 2020). As AI systems heavily rely on personal data, ensuring robust data-security measures and stringent protection laws is crucial for building public trust and preventing breaches (Bhutoria, 2022).

Policy challenges extend to data protection, security and biases inherent in AI algorithms, reflecting the complex interplay of regulatory frameworks across regions (Vincent-Lancrin & van der Vlies, 2020). Incorporating AI into learning and development faces barriers such as resistance to disruption, data availability for training algorithms and concerns about AI's efficacy for behavioural training (Dutta & Kannan Poyil, 2023). Addressing these challenges requires interactive and engaging learning experiences to meet the evolving needs of learners. This means that navigating the intricate landscape of AI-personalised learning necessitates proactive engagement. By addressing ethical dilemmas, safeguarding data security and promoting equitable access, stakeholders can harness AI's potential to reshape education and training for the betterment of all.

2.4 Conceptual Framework

To gain an understanding of what influences the acceptance of AI and its integration into personalised learning, this study utilises the TOE framework developed by Depietro et al. in 1990, alongside Senge's Learning Organisation theory, which is applied within the organisational dimension of TOE. These frameworks form the foundation of the conceptual framework designed for this study, which is driven by the influence of AI technology. Figure 2 below visualises the integration of the TOE framework and Learning Organisation theory, driven by AI technology, which impacts the technological, organisational, and environmental factors. These factors, in turn, affect the implementation of AI-enhanced personalised learning in the workplace, which is the

topic of this study. This combination of frameworks helps to measure and analyse both the dependent (influence and implementation of AI) and independent (technological, organisational and environmental elements) variables in this study. Figure 2 illustrates the proposed conceptual framework, which is guided by the research objectives (RO1, RO2, RO3). Based on this framework, hypotheses are developed to be tested in the study.

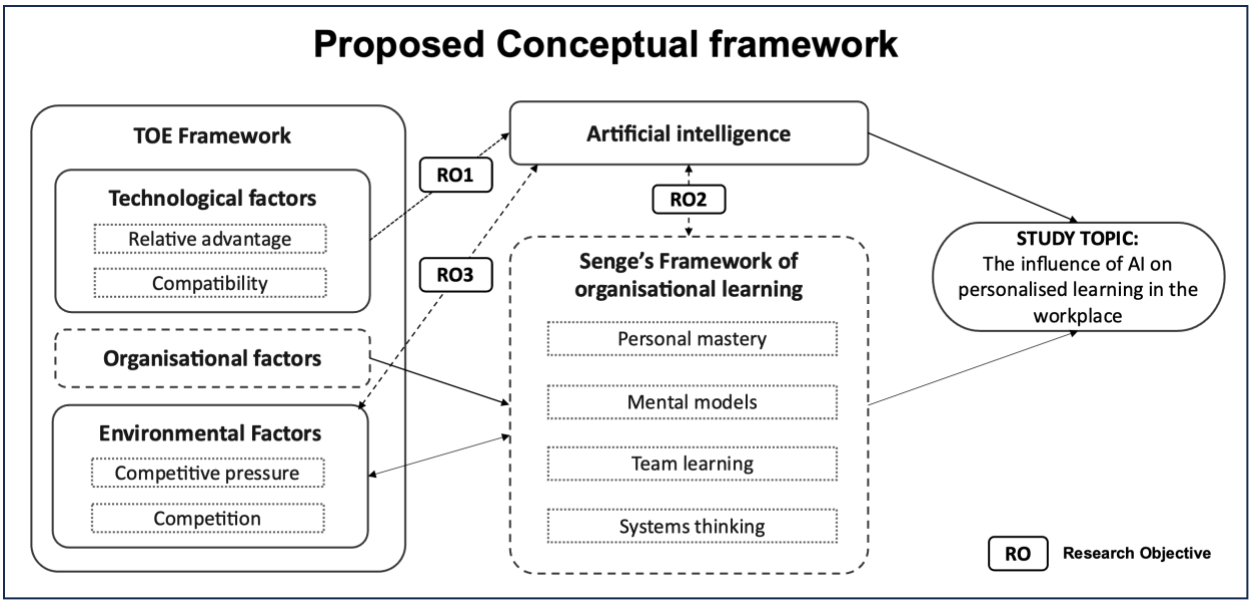

Figure 2: Proposed Conceptual Framework: The Influence of AI on Personalised Learning in the Workplace

2.4.1 Technological factors

Research Objective 1 (RO1) focuses on the exploration of the influence of AI to improve personalised learning and development in the workplace. This exploration is grounded in the TOE framework's technological dimension and aims to shed light on the importance, underpinnings and implications of AI adoption in the personalised learning landscape. The technological factors considered are relative advantage and compatibility, which are described below.

Relative advantage: The concept of relative advantage highlights the pivotal role that the perceived superiority of technological innovation over traditional methods plays in its adoption. A study by Pillai and Sivathanu (2020) emphasises this phenomenon in the recruitment realm, showcasing how AI's effectiveness accelerates talent-acquisition processes. By automating candidate evaluation and enhancing matching accuracy, AI provides a distinct competitive edge over conventional methods. Another illustration of relative advantage is cloud computing, which has reshaped IT infrastructures across sectors. Gangwar et al. (2015) highlight the superior benefits offered by cloud computing, such as cost reduction, scalability and mobility. These

advantages stand out when compared to traditional IT setups, where substantial financial investments and resource limitations are common hurdles. In the context of this study, AI's relative advantage stems from its capability to transform personalised learning experiences.

Accordingly, **Hypothesis 1** is formulated as: *The perceived relative advantage of AI-driven personalised learning over traditional methods will significantly contribute to enhancing skill development and learning experiences for employees in the workplace.*

Compatibility: The compatibility factor is used to explore the alignment between new technologies and the existing organisational fabric, with seamless integration recognised as essential for successful adoption of new technologies. This factor is evident in the AI adoption context, where new technology needs to harmonise with established systems. Gangwar et al. (2015) point to the necessity for cloud computing, for example, to integrate smoothly with an organisation's architecture and data formats. Such compatibility ensures minimal disruptions during transition and enables the leveraging of existing resources. Similarly, in an Industry 4.0 context, compatibility acquires additional significance. Srivastava et al. (2022) highlight the need for Technical Education Institutions (TEIs) to assess how Industry 4.0 technologies fit into their established IT frameworks. This evaluation reflects the technology's adaptability to the institution's processes and its potential to build upon existing infrastructure. Compatibility in this scenario becomes a pivotal determinant of successful Industry 4.0 adoption and enables organisations to capitalise on the technology's transformative potential offered in AI continuous learning opportunities within the workplace.

Accordingly, **Hypothesis 2** is formulated as: *Participants who perceive a strong compatibility between AI-driven personalised learning tools and the existing workplace structure will exhibit a greater intention to adopt these tools for personalised workplace learning and development.*

2.4.2 Organisational factors

The investigation into the second research objective (RO2) within the overall study, which highlights the importance of a continuous learning organisational work environment for personalised AI-driven learning adoption, is examined from an organisational standpoint within the TOE framework. This examination is viewed through the lens of Senge's Learning Organisation theory. This research study, guided by our research objectives, delves into four fundamental organisational factors: personal mastery, team learning, mental models, and systems thinking.

Personal mastery: Senge (2006) highlights the importance of personal mastery in fostering an environment where individuals consistently improve their skills and align their personal visions with organisational objectives. Hutasuhut et al. (2021) point to the impact of personal mastery on individual development, where self-directed learning thrives through a commitment to self-improvement and lifelong learning. Similarly, other literature reflects the significance of personal mastery in digital skill development. The modern workforce's capability to adapt to digital disruptions is contingent upon its personal mastery of digital skills (Hoe, 2019). Organisations recognise the importance of cultivating personal mastery through training and development programmes that address digital competency gaps (Hoe, 2019). This example shows how personal mastery in digital skills aligns with the broader concept of personal mastery, enhancing employees' capacity to learn and adapt.

Accordingly, **Hypothesis 3** is formulated as: *Participants who perceive alignment between their personal visions for skill improvement and the opportunities offered by AI-driven personalised learning tools within the organisational environment will exhibit a heightened intention to embrace these tools for continuous learning in the workplace.*

Team learning: Senge (2006) highlights the value of learning work teams within organisations to facilitate knowledge exchange and continuous improvement. Hutasuhut et al. (2021) write that team learning enables self-directed learning to flourish, as employees are encouraged to share insights, complement each other's skills and collectively progress. Also, various studies cite the positive influence of team learning on individual learning. Team learning facilitates the sharing of knowledge and experiences, which enables employees to learn from each other's successes and challenges (Hutasuhut et al., 2021). The significance of team learning is underscored in contexts such as the Wood Badge participation, where participants engage in group discussions and collaborative reflections to enhance their leadership skills (Marik, 2022). The collaborative dynamics fostered by team learning contribute to fostering a learning organisation.

Hence, **Hypothesis 4** is formulated as: *Organisations that prioritise team learning as a mechanism for collaborative skill development within a continuous learning organisational culture will be more inclined to adopt AI-driven personalised learning tools for their employees.*

Mental models: Senge (2006) accentuates the importance of bringing tacit mental models to the surface to encourage learning and the refinement of thinking. Hoe (2019) highlights the necessity for organisations to challenge existing mental models to adapt to digital disruptions effectively.

Research examples reveal the transformative potential of challenging mental models. Organisations that aim to thrive in the digital revolution must "rewire" their thought processes to align with human-centric design thinking (Hoe, 2019). Marik's examination of stereotypes and perceptions through Wood Badge participation showcases the evolution of mental models over time and their alignment with leadership improvement goals (Marik, 2022). The role of mental models extends beyond individual perspectives to encompass organisational paradigms that influence decision-making and innovative strategies.

Thus, **Hypothesis 5** is formulated as: *Participants who have undergone shifts in their mental models through prior learning and development programmes will demonstrate a heightened readiness to embrace AI tools that facilitate ongoing learning opportunities within a continuous learning organisational environment.*

Systems thinking: Senge (2006) highlights systems thinking as a way of understanding the broader context in which organisational components function together. This holistic approach aids decision-making and fosters adaptability within dynamic environments. Findings from various studies accentuate the value of systems thinking in organisations. Participants' ability to recognise themselves as part of a larger interconnected system and thus exhibit systems thinking will have an impact on facilitating collaborative and adaptive behaviours (Hutasuhut et al., 2021). Organisations that embrace systems thinking cultivate an environment where decisions are grounded in a holistic view of events, fostering effective and flexible decision-making (Al-Dhuwaihi et al., 2020).
Hence, **Hypothesis 6** is formulated as: *Participants who value a holistic perspective shaped by systems thinking will exhibit greater receptivity to AI-driven personalised learning tools within a continuous learning organisational work environment***.**

2.4.3 Environmental factors

The third research objective (RO3), which relates to the environmental dimension within the TOE framework, seeks to investigate external influences that impact a firm's intention to adopt technology. This discussion explores two pivotal environmental factors: regulatory support and competitive pressure.

Regulatory support: The regulatory environment can either encourage or constrain technological innovation according to the nature of the regulations. Government policies and initiatives impact technology adoption. The government's role in promoting innovation, as seen in programmes such as "Make in India" and "Digital India", underscores the importance of regulatory support in shaping the technology adoption landscape (Pan et al., 2022). The influence of government support on technology adoption is evident in various contexts. Studies on corporate website adoption and ERP systems confirm the role of perceived government support in influencing adoption decisions (Srivastava et al., 2022). Government policies and initiatives, such as Industry 4.0 and new education policies, are recognised as catalysts for technology adoption as they promote the integration of modern technologies in pedagogy (Srivastava et al., 2022). Regulatory support is pivotal in creating an enabling environment that fosters innovation and adoption.

Thus, **Hypothesis 7** is formulated as: *A supportive regulatory environment that fosters technological innovation and adoption will positively influence attitudes toward AI-driven personalised learning tools in the workplace.*

Competitive pressure: The pressure that firms encounter from competitors within the industry drives them to adopt new technologies to meet competitive standards. The significance of competitive pressure is especially pronounced when new technologies directly impact the competitive dynamics of the market (Gangwar et al., 2015). The role of competitive pressure in motivating technology adoption is evident in several studies (Chen et al., 2021; Gangwar et al., 2015). Firms recognise that adopting innovative technologies alters industry structure, redefines competitive rules and provides advantages over rivals (Chen et al., 2021). Cloud computing, for instance, demonstrates the importance of adopting new technologies to transform the competitive environment, enhance operational efficiencies and achieve market visibility (Tongsuksai et al., 2023). Competitive pressure acts as a driving force that compels organisations to adopt AI technologies to gain a competitive edge (Gupta et al., 2022). The competitive landscape influences organisations to implement technological advancements to remain aligned with industry norms and strategic necessities.

Thus, **Hypothesis 8** is formulated as: *Competitive pressures that drive organisations to adopt innovative technologies in order to meet industry standards will have a positive impact on employees' attitudes toward AI-driven personalised learning tools in the workplace.*

2.5 Conclusion of Literature Review

This literature review provided an in-depth exploration of the study's background, and then examined the study through the perspectives of two theoretical frameworks, Depietro et al. TOE framework and Senge's Learning Organisation theory. Subsequently, a conceptual framework was developed by integrating these two frameworks, leading to the formulation of the following hypotheses.

H1: *The perceived relative advantage of AI-driven personalised learning over traditional methods will significantly contribute to enhancing skill development and learning experiences for employees in the workplace.*

H2: *Participants who perceive a strong compatibility between AI-driven personalised learning tools and the existing workplace structure will exhibit a greater intention to adopt these tools for personalised workplace learning and development.*

H3: *Participants who perceive alignment between their personal visions for skill improvement and the opportunities offered by AI-driven personalised learning tools within the organisational environment will exhibit a heightened intention to embrace these tools for continuous learning in the workplace.*

H4: *Organisations that prioritise team learning as a mechanism for collaborative skill development within a continuous learning organisational culture will be more inclined to adopt AI-driven personalised learning tools for their employees.*

H5: *Participants who have undergone shifts in their mental models through prior learning and development programmes will demonstrate a heightened readiness to embrace AI tools that facilitate ongoing learning opportunities within a continuous learning organisational environment.*

H6: *Participants who value a holistic perspective shaped by systems thinking will exhibit greater receptivity to AI-driven personalised learning tools within a continuous learning organisational work environment.*

H7: *A supportive regulatory environment that fosters technological innovation and adoption will positively influence attitudes toward AI-driven personalised learning tools in the workplace.*

H8: *Competitive pressures that drive organisations to adopt innovative technologies in order to meet industry standards will have a positive impact on employees' attitudes toward AI-driven personalised learning tools in the workplace.*

Chapter 3: Research Methodology

This chapter sets out the methodology of this research. The chapter begins by articulating the research approach and design and then moves on to describing the data-collection and -analysis methods, the limitations of the study, and the strategies used for ensuring the quality and ethical integrity of the study.

3.1 Research Purpose

The research aimed to explore how AI can augment individual learning within the workplace context. This investigation was structured around three core research objectives: firstly, to examine the potential of AI in fostering individualised learning trajectories and development opportunities; secondly, to understand the significance of cultivating a continuous learning environment within organisations for the adoption of personalised AI-driven learning modalities; and thirdly, to identify and analyse the critical factors that influence the integration and effectiveness of personalised AI-driven learning strategies in workplace settings. Through analysis, the study aimed to contribute to the scholarly discourse on the strategic implementation of AI for personalised learning endeavours in the workplace. By exploring the benefits and constraints of AI applications for professional development, the research sought to provide meaningful insights for organisations aspiring to harness AI technologies to support and enhance personalised learning and development initiatives.

3.2 Research Approach

The research adopted a quantitative approach to investigate the impact of AI on personalised workplace learning. A quantitative approach was chosen because it allows for the systematic collection and analysis of data from a large sample, providing statistically significant results that can be generalized to a broader population. This approach is particularly suitable for examining the relationships between variables, such as the extent of AI integration and its effects on learning outcomes. However, it is important to acknowledge the limitations of a quantitative approach, such as the potential for reduced depth of understanding compared to qualitative methods. To mitigate this, the study employs robust data collection and analysis techniques to ensure the reliability and validity of the findings. A deductive research strategy was employed, which was grounded in the TOE framework (Depietro et al., 1990) and Senge's Learning Organisation theory (Senge, 2006). This strategy began with the application of established theoretical frameworks and hypotheses, followed by the collection and analysis of data to confirm or to refute these

hypotheses. The methodology focused on gathering and analysing numerical data to explore the correlation between AI-enhanced personalised learning and various factors within the workplace.

3.3 Research Design

The investigation of the research utilised a survey that was distributed through email with the survey link to a website that used an AI-powered chatbot survey interface. Developed on the basis of Lohman's (2006) previous research, the survey aimed to quantify employees' engagement with informal learning activities, their perceptions of AI-enhanced personalised learning and the factors that influenced their perceptions. For the purpose of this study, the survey provided an AI chatbot interface as a novel and engaging way for participants to interact with the survey, which was expected to increase participant involvement and yield more precise insights, despite its potential technical challenges and biases. The chatbot interface offered a unique and engaging survey experience, potentially increasing response rates and maintaining participant interest. It allowed for personalised interactions, which increased the potential for precise insights and made the survey process more accessible and user-friendly. The survey was conducted through a platform hosted on Google Sites. The platform featured an introductory message that outlined the research objectives, accompanied by a brief video that elucidated the premise of the research. Positioned beneath these introductory elements was the AI-powered survey chatbot, designed to navigate participants through the survey questions in a format that was both personalised and engaging. This methodological approach aimed to enhance participant engagement by providing a more interactive and user-friendly survey experience.

3.4 Data-Collection Methods

The survey was administered to 391 participants across several employment sectors. The data-collection process was facilitated using the online survey/chatbot platform, which ensured efficient data management.

3.5 Population and Sample

The research targeted employees across various organisations that were exposed to AI-enabled technologies in the workplace, specifically focusing on those participating in professional growth and learning initiatives within their respective work environments. In addition, a purposive sampling method was used, targeting a diverse sample to reflect different demographics and provide a comprehensive view of AI's impact on personalised learning. The survey was

disseminated among a diverse cohort, encompassing more than 14,000 individuals, including postgraduate students, academic staff, and professionals. It garnered participation from a total of 391 respondents, culminating in a response rate of approximately 2.79%. This response provided a substantial dataset for the quantitative analysis in this study.

3.6 The Research Instrument

The survey instrument, which was designed to explore the influence of AI on personalised learning within the workplace, was crafted to align with the study's research objectives, underpinned by literature and the theoretical frameworks used as a foundation for the study. Utilising a 5-point Likert scale (Carifio & Perla, 2007), the survey consisted of five sections as described below. The research instrument is attached to this report as Appendix A.

Section 1: Demographics – This initial section collected demographic information from participants, including age, gender, type of industry and years of experience. This allowed for an analysis of responses segmented according to these characteristics.

Section 2: Perception of Artificial Intelligence in Workplace Learning – In this part of the survey, participants' perceptions of AI-enabled personalised learning were explored. Questions assessed their familiarity with AI technologies, the perceived benefits of AI-enhanced learning and any concerns regarding its implementation.

Section 3: Engagement in Informal Learning – This segment investigated how participants engaged with informal learning activities within their workplace, focusing on the extent to which AI facilitated this engagement.

Section 4: Artificial Intelligence Implementation – Questions here delved into the experiences of participants with AI implementation at their workplaces, evaluating factors that either hindered or promoted successful AI integration. This section aimed to connect responses with the technological, organisational and environmental dimensions of the TOE framework.

Section 5: Hypotheses Testing – The final section directly targeted the research hypotheses, gathering data on AI's relative advantage, compatibility, personal mastery, team learning, mental models, systems thinking, regulatory support and competitive pressure.

The chosen survey design with its inclusion of an AI-powered chatbot survey interface facilitated a systematic and engaging investigation of the research questions. It allowed for quantitative data collection, enabling statistical comparisons and analyses. However, it is important to note the limitations such as potential response bias and the simplification of complex opinions that are inherent in self-reported survey data and Likert-scale questions. Despite these challenges, the research instrument effectively captured a comprehensive outlook of the influence of AI on personalised learning in the workplace.

3.7 Procedure for Data Collection

A streamlined methodological approach was designed to increase accessibility and participation ease for participants, with the data-collection procedure following participant selection and the survey development. With ethical approval secured from the Wits Post-Graduate Committee (PGC) and permission received from the departments approached for data collection, emails were sent to postgraduate students and staff members within the University of the Witwatersrand to participate in the survey, attached to this report as Appendix C and D. The email contained a brief summary of the research and a link to the website with the chatbot survey. A covering message on the website informed participants about the study's purpose, their rights and the ensured confidentiality of their responses. The website also included a video detailing the research in case participants chose not to read the cover message. All the data entered from the chatbot survey went into an online Microsoft Excel document.

3.8 Data-Analysis Strategies and Interpretation

For the quantitative data obtained from the survey, descriptive statistics and inferential analysis techniques, such as linear regression analysis, were used to examine the relationships between the variables in the hypotheses (Merriam & Tisdell, 2015). Descriptive statistics provide a summary of the data, highlighting key trends and patterns, while inferential techniques like linear regression allow for the testing of hypotheses and the examination of relationships between variables. Linear regression was chosen for its ability to model the relationship between the dependent variable and independent variables. The analysis was conducted using the Statistical Programme for Social Sciences (SPSS), which enabled the examination of correlations between various dimensions and their impact on personalised learning outcomes. The results were interpreted within the TOE theoretical framework and Senge's Learning Organisation theory.

3.9 Limitations and Challenges of the Study

The study acknowledges several limitations and challenges that could potentially affect the research outcomes. These include a reliance on self-reported data, which might lead to response bias, and the limitations inherent in using Likert-scale surveys (see Section 3.6 above). Additionally, the response rate and the very limited timeframe for data collection and analysis were identified as potential factors that might affect the comprehensiveness of the results.

3.10 Quality Assurance and Ethics

To uphold the study's quality, representative sampling was employed to enhance external validity by ensuring a broad and inclusive participant base; pilot testing of the survey tool was conducted to confirm its reliability through consistent measurements; and adequate research design choices were made to establish internal validity and accurately measure the connections between variables, thereby minimising the influence of confounding factors, all while maintaining objectivity through unbiased data collection and analysis. Finally, ethical approval clearance was obtained from the Wits PGC prior to data collection. The research adhered to ethical standards, ensuring the integrity of the research process and the respectful and fair treatment of all participants.

3.11 Conclusion

The methodology adopted in this study provided a framework for investigating the influence of artificial intelligence (AI) on personalised learning in the workplace. By employing a quantitative approach grounded in the Technology-Organisation-Environment (TOE) framework and Senge's Learning Organisation theory, the research was able to systematically address its objectives. The use of an AI-powered chatbot survey interface, as part of the data collection method, represented an innovative approach that not only aligned with the study's focus on AI but also enhanced participant engagement and data quality. The purposive sampling method allowed for the collection of relevant and diverse insights from a sample of 391 participants across various organisations. This comprehensive methodology ensured the collection of meaningful data, setting the stage for an in-depth analysis of AI's role in facilitating personalised learning within the workplace. The careful consideration of ethical principles and quality assurance measures further underscored the study's commitment to rigor and integrity. Overall, the methodology chapter laid a foundation for exploring the complex dynamics between AI technology and learning practices in organisational settings.

Chapter 4: Presentation of Results

This chapter presents the detailed findings from the survey conducted to explore the influence of AI on personalised learning in the workplace. The data collected offers insights into the demographic distribution of the participants, their engagement in informal learning activities, the extent of AI implementation within their organisations and the empirical testing of hypotheses related to AI-driven learning.

4.1 Demographic Profile of the Participants

Sample Composition

The survey garnered responses from a total of 391 participants who represented a diverse range of industries, ages, genders and years of experience. The composition of the sample is detailed below and provides insights into the demographic makeup of the participants.

Gender Distribution

Of the 391 participants, 152 identified as male (38,9%) and 239 as female (61,1%).

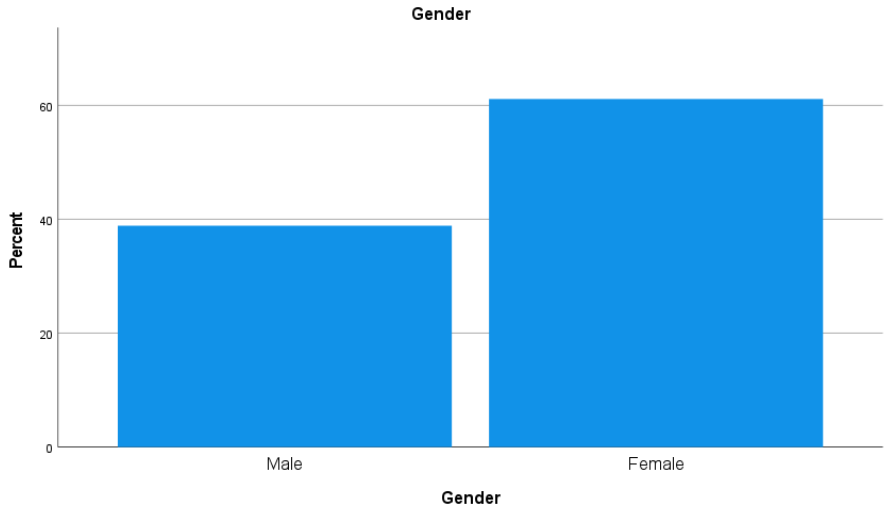

Figure 3: The Gender Distribution of the Participants in Percentage (%)

Age Range

The participants' ages were categorised into five groups, revealing the following distribution:

- 18–24 years: 12% (n=47)
- 25–34 years: 40,2% (n=157)
- 35–44 years: 31,7% (n=124)
- 45–54 years: 15,3% (n=60)
- 55 years and above: 0,8% (n=3)

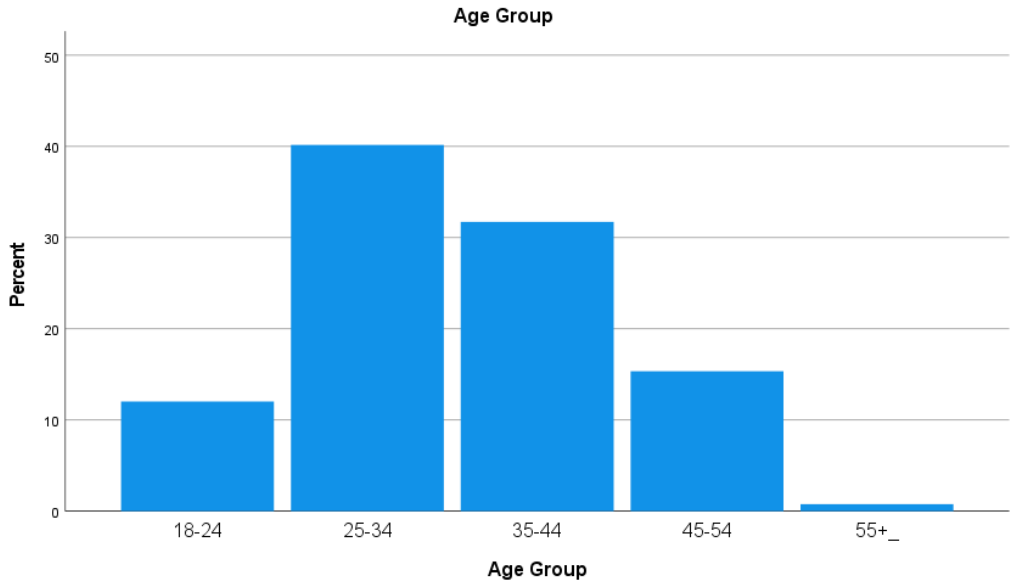

Figure 4: The Age Range of Participants in Percentage (%)

The age distribution was predominantly within the 25-34 year age bracket (40.2%), followed by the 35-44 year group (31.7%). This suggests a relatively young and middle-aged cohort, which may influence their familiarity and engagement with AI technologies.

Years of Experience

Regarding professional experience, the participants' years in the workforce were categorised as follows:

- Less than 1 year: 5,6% (n=22)
- 1–5 years: 28,6% (n=112)
- 6–10 years: 33,8% (n=132)
- 11–15 years: 23,5% (n=92)
- More than 15 years: 8,4% (n=33)



Figure 5: Years of Experience of the Participants in Percentage (%)

Participants' years of experience varied, with the highest percentage (33.8%) having 6-10 years of professional experience, indicating a sample with substantial work experience. The varying years of experience and diverse industry backgrounds (finance, healthcare, education, and technology) add to the richness of the data.

Industry Representation

Participants reported employment across various industries, with the highest representation seen in the following sectors:

- Information Technology: 5,9% (n=23)
- Healthcare: 6,9% (n=27)
- Education: 27,6% (n=108)
- Finance: 5,4% (n=21)
- Another 21 sectors (including banking and engineering): 54,2% (n=212)

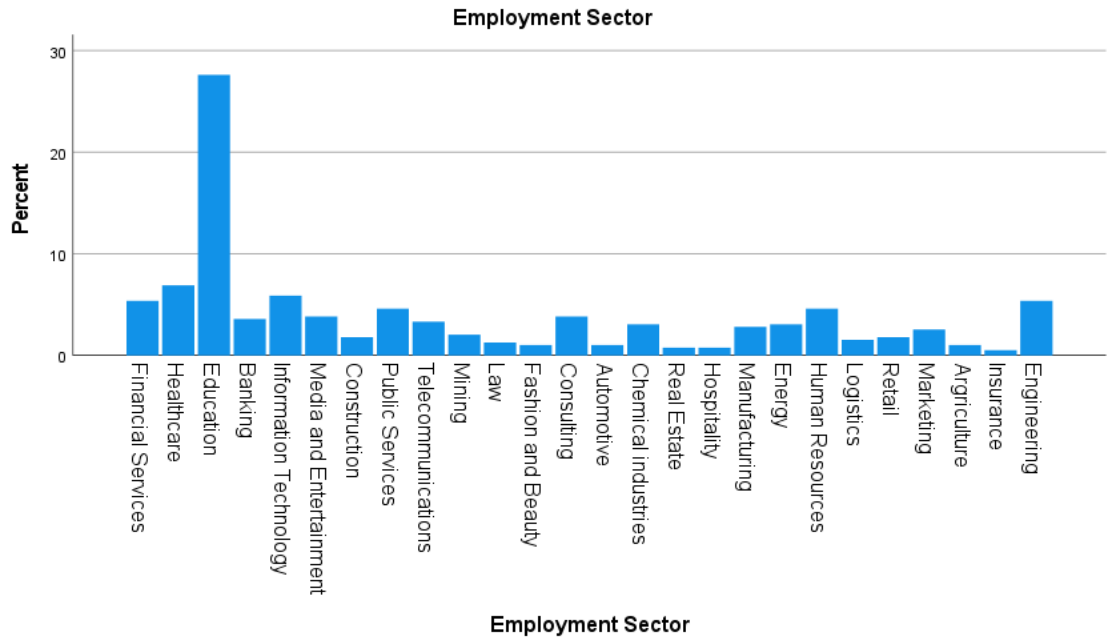

Figure 6: Representation of Participants' Employment Industries in Percentage (%)

Industry representation showed a significant concentration in education (27.6%), highlighting the sector's interest in AI-driven personalised learning. These demographic insights are crucial for understanding the contextual factors that may affect participants' perceptions and engagement with AI technologies. Furthermore, the demographic profile of the study participants indicated that they were exclusively from South Africa.

4.2 Perception of Artificial Intelligence in Workplace Learning

For a detailed understanding of the specific questions that informed the analysis (e.g., (Q5), (Q6) and (Q7)), these questions are found in Appendix A. This appendix contains the full list of survey questions that served as the foundation for the investigation, providing insights into the data collection process and the variables measured in this study.

Descriptive Statistics

The survey data provided quantifiable insight into the participants' perceptions of AI in the workplace, as summarised in Table 1. This table shows the mean scores and standard deviations of the familiarity with AI technologies (Q5); perceived benefits of AI-enhanced learning (Q6); and concerns about AI implementation (Q7) variables.

Table 1: Summary Statistics of Key Variables

Variable	Mean	SD
(Q5) Familiarity with AI technologies	3.06	1.23
(Q6) Perceived benefits of AI-enhanced learning	3.51	1.185
(Q7) Concerns about AI implementation	2.52	1.3

Participants reported a moderate level of (Q5) familiarity with AI technologies (M = 3.06, SD = 1.23), indicating a slightly above-neutral familiarity on the five-point Likert scale used. The (Q6) perceived benefits of AI to improve and create personalised learning experiences were viewed more favourably (M = 3.51, SD = 1.185), suggesting that the majority of participants recognised the potential advantages of integrating AI into learning processes. Conversely, (Q7) concerns about AI implementation were less pronounced (M = 2.52, SD = 1.3), which reflects a lower level of concern regarding the adoption of AI technologies in workplace learning environments.

These findings suggest a cautiously optimistic view among the workforce regarding AI's role in enhancing learning and development opportunities. The relatively higher mean score for the perceived benefits compared to the familiarity with AI technologies and concerns about AI implementation may indicate a recognition of AI's potential despite a moderate level of current familiarity and some underlying reservations about its implementation. The standard deviations indicate a moderate spread in responses, pointing to diverse opinions among participants.

Correlation Analysis

The interrelationships between participants' familiarity with AI technologies, perceived benefits of AI-enhanced learning and concerns about AI implementation were examined using Pearson's correlation coefficient. The results are presented in Table 2 below.

Table 2: Pearson Correlation Matrix for Continuous Variables

Variable	1	2	3
1. Familiarity with AI technologies	-		
2. Perceived benefits of AI-enhanced learning	.050	-	
3. Concerns about AI implementation	-1.64	-.017	-

The analysis revealed a statistically significant negative correlation between familiarity with AI technologies and concerns about AI implementation ($r = -1.64$, $p < .01$), indicating that as familiarity with AI technologies increases, concerns about AI implementation decrease. This strong negative relationship underscores the potential role of familiarity in alleviating concerns regarding AI in the workplace.

Conversely, the perceived benefits of AI-enhanced learning showed no significant correlation with familiarity with AI technologies ($r = .050$, $p > .05$), suggesting that the perceived benefits are not dependent on the level of familiarity with the technology. Additionally, no significant relationship was identified between the perceived benefits of AI-enhanced learning and concerns about AI implementation ($r = -.017$, $p > .05$). This indicated that recognising the benefits of AI does not necessarily correlate with the level of concern regarding its implementation.

These findings suggest that increasing familiarity with AI technologies may be key to reducing concerns about AI, while the perceived benefits of AI-enhanced learning appear to be independently formed and are not directly associated with levels of familiarity or concern.

4.3 Engagement in Self-Directed Learning

Descriptive Statistics

The survey investigated key factors related to the use of AI-driven personalised learning tools and their perceived importance for skills development in the workplace. Table 3 presents the mean scores and standard deviations for (Q8) the frequency of engagement in self-directed learning activities; (Q9) the adoption of AI-driven personalised learning tools; and (Q10) the perceived importance of self-directed learning for skills development in the workplace.

Table 3: Summary Statistics of Key Variables regarding Engagement in Self-Directed Learning

Variable	Mean	SD
(Q8) Frequency of engagement in self-directed learning activities	3.50	1.03
(Q9) Adoption of AI-driven personalised learning tools	3.31	1.2
(Q10) Importance of self-directed learning for skills development in the workplace	3.71	1.188

The frequency of engagement in self-directed learning activities reported by the participants indicated a moderately high level of engagement, with a mean score of 3.50 (SD = 1.03). This suggests that on average, participants often engaged in learning activities independently, which is indicative of a proactive approach to professional development.

In terms of adoption, the AI-driven personalised learning tools received a mean score of 3.31 (SD = 1.2), which is above the midpoint of the scale, reflecting a moderate level of adoption among the participants. The standard deviation indicates a moderate variability in responses, suggesting different rates of adoption among participants.

Furthermore, the perceived importance of self-directed learning for skills development in the workplace was rated highly, with a mean score of 3.71 (SD = 1.188). This high score points to the value that the participants placed on autonomous learning as a critical component of their professional growth.

The reported means suggest that while there was an established engagement with and recognition of the value of self-directed learning, the adoption of AI-driven tools for this purpose was still in the moderate range. The variability in scores, as indicated by the standard deviations, points to a diverse set of experiences and perceptions among the workforce regarding both the adoption of these tools and the extent to which self-directed learning was emphasised within their organisations.

These findings imply a potential gap between the recognition of the importance of self-directed learning for skills development and the actual adoption of innovative tools designed to support this type of learning. The data sets the stage for further analysis to understand the barriers to adoption and to develop strategies that may increase the use of AI-driven tools in the workplace.

Regression Analysis

A linear regression analysis was performed to evaluate the predictive power of the adoption of AI-driven personalised learning tools over employees' engagement in self-directed learning activities. The aim was to ascertain the extent to which the adoption of these tools could explain the variance in self-directed learning engagement.

The regression model was statistically significant, $F(1, 389) = 16.93$, $p < .01$, suggesting that the adoption of AI-driven tools is a significant predictor of engagement in self-directed learning. The coefficient of determination, R^2, was .42, which indicated that approximately 42% of the variability in engagement in self-directed learning can be accounted for by the level of adoption of AI tools. The adjusted R^2 of .39 adjusts this figure for the number of predictors in the model, which in this case is one, and suggests a robust model fit.

This significant model suggests that as the adoption of AI-driven personalised learning tools increases, so does the engagement in self-directed learning. This finding implies that there is a substantial and meaningful association between the use of AI tools and the active engagement of employees in their own learning processes.

Given the magnitude of the R^2 value, it can be inferred that the adoption of AI-driven tools plays a crucial role in promoting self-directed learning among employees. The results support the contention that investment in and encouragement of AI tool usage could be a strategic approach to enhancing self-directed learning initiatives within organisations.

4.4 Artificial Intelligence Implementation

Descriptive Statistics

An analysis of the factors influencing the implementation of AI in the workplace revealed a range of perceptions among participants, as summarised in Table 4.

Table 4: Summary Statistics of Key Variables regarding AI Implementation

Variable	Mean	SD
(Q11) Technological factors	3.17	1.246
(Q12) Organisational factors	3.41	1.086
(Q13) Environmental factors	3.67	1.207

Technological factors (Q11), which encompass the technical readiness and the presence of AI tools, had a mean score of 3.17 (SD = 1.246). This score suggests a moderate level of technological readiness within organisations as perceived by the participants.

Organisational factors (Q12), which refer to the internal support and processes that facilitate AI integration, were rated slightly higher, with a mean of 3.41 (SD = 1.086). This indicates a somewhat positive perception of the organisational preparedness and support for AI initiatives.

Environmental factors (Q13), reflecting the broader context that includes regulatory support and industry trends, received the highest mean score of 3.67 (SD = 1.207). This score points towards a recognition of favourable external conditions for AI adoption within the industry.

The standard deviations for all three factors indicate a moderate spread in the responses, reflecting diversity in the participants' experiences and perceptions. Notably, the environmental factors showed a relatively broader dispersion of responses, hinting at varied external influences on AI implementation across different workplaces.

These statistics suggest that while there is a general acknowledgment of the importance of technological, organisational and environmental factors in AI adoption, there is a nuanced

spectrum of experiences among individuals. This could be reflective of the varying stages of AI integration across different organisations and sectors.

Correlation Analysis

To understand how technological, organisational and environmental factors are interrelated in the context of AI implementation, Pearson's correlation analysis was conducted. The results, as depicted in Table 5, provide insights into the dynamics between these elements.

Table 5: Pearson Correlation Matrix for Continuous Variables regarding AI Implementation

Variable	1	2	3
4. Technological factors	-		
5. Organisational factors	.549	-	
6. Environmental factors	-.022	-.097	-

A statistically significant positive correlation was found between technological and organisational factors ($r = .549$, $p < .01$), suggesting that improvements in technological readiness are associated with stronger organisational support for AI initiatives. The magnitude of this correlation indicates a moderate to strong relationship, which implies that as organisations improve their technological capabilities, there tends to be a concomitant increase in organisational processes and structures that support AI integration.

Conversely, the correlation between technological factors and environmental factors was not statistically significant ($r = -.022$, $p > .05$), nor was the correlation between organisational and environmental factors ($r = -.097$, $p > .05$). These non-significant relationships suggest that the participants did not perceive a direct link between the environmental context of AI implementation and the technological and organisational readiness within their workplaces.

The results highlight the central role of organisational dynamics in leveraging technological advancements for AI implementation. The lack of significant correlations with environmental factors may indicate that internal company strategies and capabilities are seen as more immediately relevant to AI implementation success than external environmental conditions.

4.5 Results pertaining to Hypotheses 1–8

To test these hypotheses, the research employed quantitative analysis methods, including descriptive statistics, Pearson's correlation analysis, and linear regression models. These statistical techniques enabled the research to uncover the depth of AI's influence across various dimensions, such as its perceived benefits, compatibility with workplace structures, and its role in fostering a continuous learning environment.

4.5.1 Hypothesis 1 (H1): Inferential Statistics

The first hypothesis (H1) states that employees' perceived improvement by AI in self-directed learning (Independent Variable: Q6) will significantly predict the effectiveness of AI-driven personalised learning compared to traditional methods (Dependent Variable: Q14). The null hypothesis (H0) for this relationship states that the perceived improvement by AI does not predict the effectiveness of AI-driven personalised learning, indicating no association between these variables.

Table 6: Reliability Statistics for H1

Independent Variable	Dependent Variable	Cronbach Alpha
Familiarity with AI (Q6)	Learning Tools (Q14)	0.797

Prior to testing this hypothesis through regression analysis, the internal consistency of the scale used to measure perceived improvement by AI was assessed. A Cronbach's Alpha value of 0.797 was obtained for the independent variable (Q6), which indicates good reliability. This suggests that the items used to measure perceived improvement by AI are consistent and reliable in this context as illustrated in Table 6 above.

A simple linear regression was computed to predict the effectiveness of AI-driven personalised learning based on the perceived improvement by AI. The regression model was significant, $F(1, 389) = 196.904$, $p < 0.01$, explaining 44.4% of the variance in the effectiveness of AI-driven personalised learning ($R^2 = 0.444$, Adjusted $R^2 = 0.443$). This result suggests a strong positive relationship between perceived improvement by AI and the perceived effectiveness of AI-driven personalised learning.

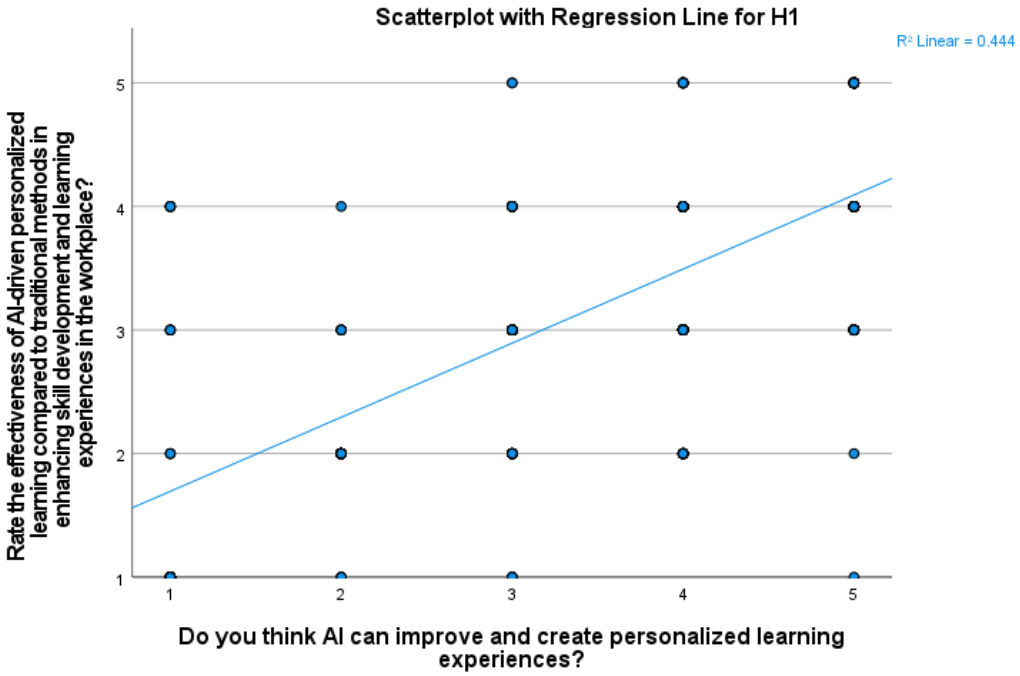

Figure 7: Scatterplot with Regression Line for H1

The scatterplot shown in Figure 7 illustrates a positive linear relationship, which indicates that approximately 44.4% of the variability in the perceived effectiveness of AI-driven personalised learning is explained by the extent to which participants believe AI can enhance learning experiences.

The regression equation, Y = 0.6X + b, where "Y" represents the effectiveness of AI-driven personalised learning and "X" represents the perceived improvement by AI, shows that for every one-unit increase in the perceived improvement by AI, there is a corresponding 0.6-unit increase in the perceived effectiveness of AI-driven personalised learning.

The regression coefficient (B = 0.6) was found to be statistically significant, $t(389) = 17.64$, $p < 0.01$. This provides substantial evidence to reject the null hypothesis and support the alternative hypothesis that the perceived improvement by AI is a significant predictor of the effectiveness of AI-driven personalised learning. Table 7 below presents a full summary of the regression coefficients for the two variables.

Table 7: Regression Coefficients for H1

Variable	B	95%CI	β	t	p
Constant	1.095	[.85, 1.34]	-	8.688	<.001
Familiarity with AI (Q6)	.6	[.53, .67]	.667	17.64	<.001

Note. Constant = 0.6, $F(1, 389) = 196.904$, $p < 0.01$, $R^2=0.44$

Given the significant p-value and the substantial proportion of variance explained by the model, the alternative hypothesis is supported, indicating that perceptions of AI's role in improving learning are indeed associated with its perceived effectiveness in comparison to traditional learning methods.

4.5.2 Hypothesis 2 (H2): Inferential Statistics

Hypothesis 2 (H2) proposes that a perceived strong compatibility between AI-driven personalised learning tools and existing workplace structures will positively influence employees' intentions to adopt these tools. Conversely, the null hypothesis (H0) states that there is no relationship between the perceived compatibility (Q15) and the intention to adopt AI-driven personalised learning tools (Q9).

Table 8: Reliability Statistics for H2

Independent Variable	Dependent Variable	Cronbach Alpha
Compatibility with AI (Q15)	Intention to adopt (Q9)	0.765

The scale used to measure the perceived compatibility (Q15) demonstrated good internal consistency, with a Cronbach's Alpha of 0.765. This suggests that the items within the scale are reliably measuring the construct of compatibility and that they produce consistent results.

A linear regression was conducted to predict the intention to adopt AI-driven tools on the basis of their perceived compatibility. The model was highly significant, $F(1, 389) = 247.58$, $p < 0.001$, indicating that compatibility is a strong predictor of adoption intention. The coefficient of determination, R^2, was 0.389, with an adjusted R^2 of 0.387, which means that approximately 38.9% of the variance in the intention to adopt AI-driven tools is explained by the perceived compatibility of these tools with existing workplace structures.

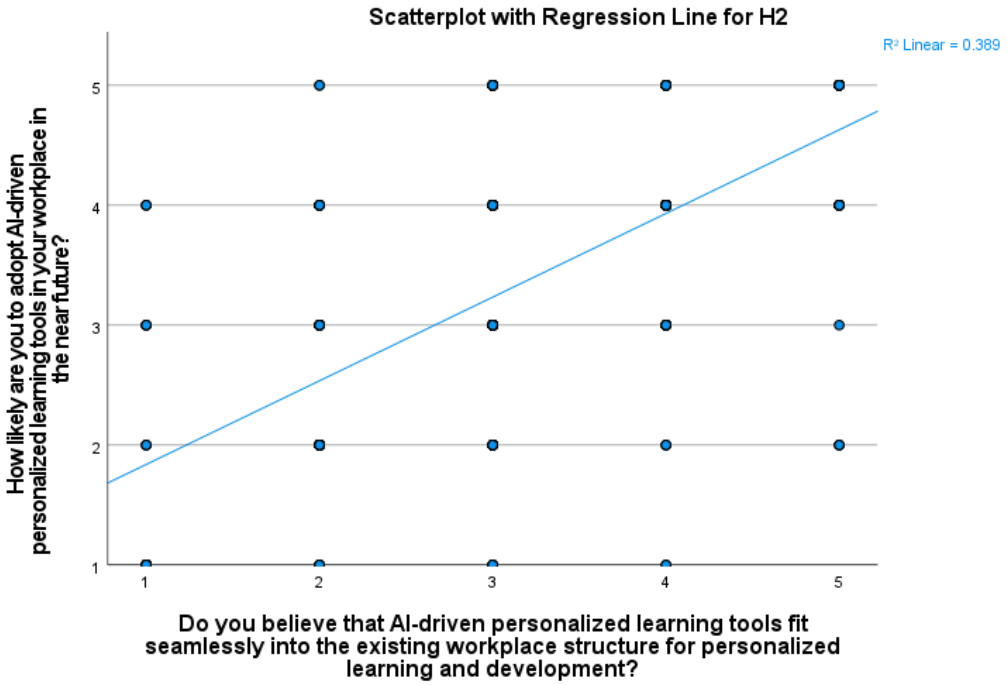

Figure 8: Scatterplot with Regression Line for H2

The scatterplot above presents a positive correlation, as evidenced by an R-squared value of 0.389. This value indicates the significance of compatibility in the decision to implement AI solutions in the workplace.

The regression coefficient (B = .698) indicates a substantial positive effect, with a t-value of 15.735, $p < 0.001$. This means that for every one-unit increase in perceived compatibility, there is an associated 0.698-unit increase in the intention to adopt AI-driven tools. Table 9 below presents a full summary of the regression coefficients for the two variables.

Table 9: Regression Coefficients for H2

Variable	B	95%CI	β	t	p
Constant	1.141	[.85, 1.42]	-	7.815	<.001
Compatibility with AI (Q15)	.698	[.61, .76]	.475	15.735	<.001

Note. Constant = 0.698, $F(1, 389) = 247.58$, $p < 0.01$, $R^2=0.389$

The results provide strong evidence in support of the alternative hypothesis (H2), suggesting that the more compatible employees perceive the AI-driven tools to be with their workplace structure, the higher their intention to adopt these tools will be. The statistically significant regression model,

along with the high R^2 value and the substantial regression coefficient, affirms that compatibility is not only a significant factor but also a meaningful predictor of employees' adoption intentions.

Given the magnitude of the effect and the statistical significance, the null hypothesis (H0) can confidently be rejected in favour of the alternative hypothesis (H2). This underscores the importance of ensuring that AI-driven personalised learning tools align well with existing workplace structures to facilitate their adoption.

4.5.3 Hypothesis 3 (H3): Inferential Statistics

Hypothesis 3 (H3) posits that individuals who perceive a strong alignment between their personal visions for skill improvement and AI-driven personalised learning tools will be more likely to embrace these tools for continuous learning. The corresponding null hypothesis (H0) is that there is no relationship between the perceived alignment of AI-driven personalised learning tools with personal skill development goals and the intention to adopt these AI-driven learning tools.

Table 10: Reliability Statistics for H3

Independent Variable	Dependent Variable	Cronbach Alpha
Alignment with personal vision (Q16)	Intention to adopt (Q9)	0.693

The scale comprising the items from Q16 (perceived alignment with personal skill improvement goals) and Q9 (intention to adopt AI-driven personalised learning tools) demonstrated good internal consistency, with a Cronbach's Alpha of 0.693. This suggests that the scale items are sufficiently correlated to form a reliable measure, which indicates that participants provided consistent responses across these items.

A linear regression analysis was conducted to predict the intention to adopt AI-driven personalised learning tools (Q9), based on the perceived alignment with personal skill improvement goals (Q16). The regression model was statistically significant, $F(1, 389) = 34.6$, $p < 0.01$, indicating that perceived alignment is a predictor of the intention to adopt AI tools. The R-squared value of 0.082 suggests that approximately 8.2% of the variance in the intention to adopt AI-driven tools can be explained by the perceived alignment with personal skill development goals, with the adjusted R-squared value of 0.079 confirming the strength of this model after accounting for the number of predictors.

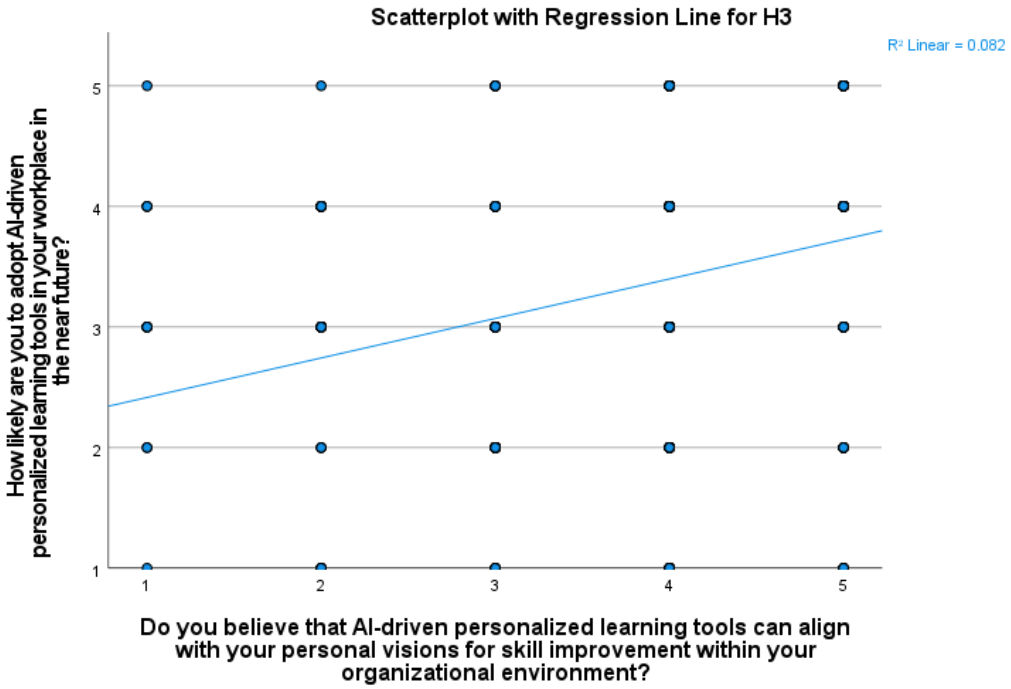

Figure 9: Scatterplot with Regression Line for H3

The scatterplot above depicts a positive linear association, as indicated by an R-squared value of 0.082. This points to the relevance of personal vision congruence in the acceptance of AI learning innovations.

The regression coefficient (B = .328) indicates that as the perceived alignment increases by one unit, the intention to adopt AI-driven tools increases by 0.328 units, holding all other variables constant. This effect was found to be significant, $t(389) = 5.882$, $p < 0.01$. Table 11 below presents a full summary of the regression coefficients for the two variables.

Table 11: Regression Coefficients for H3

Variable	B	95%CI	β	t	p
Constant	2.088	[1.66, 2.51]	-	9.665	<.001
Alignment with personal vision (Q16)	.328	[.22, .44]	.624	5.882	<.001

Note. Constant = 0.328, $F(1, 389) = 34.6$, $p < 0.01$, $R^2=0.082$

The positive and statistically significant regression coefficient for Q16 supports the alternative hypothesis (H3), suggesting that individuals who perceive a greater alignment of AI-driven tools with their personal learning goals are more likely to intend to adopt these tools. The statistical

significance of the model and the positive coefficient provide evidence to reject the null hypothesis (H0) in favour of H3.

The findings imply that personal relevance and the perceived utility of AI tools in achieving personal learning objectives are important factors in influencing the adoption of such technologies. This underscores the importance of aligning AI-driven learning initiatives with individual professional development goals to enhance their acceptance and utilisation.

4.5.4 Hypothesis 4 (H4): Inferential Statistics

Hypothesis 4 (H4) proposes that organisations that prioritise team learning will be more inclined to adopt AI-driven personalised learning tools. The null hypothesis (H0) for this scenario posits that there is no significant relationship between the prioritisation of team learning and the adoption of AI-driven tools in the workplace.

Table 12: Reliability Statistics for H4

Independent Variable	Dependent Variable	Cronbach Alpha
Team learning prioritisation (Q17)	integration of AI (Q12)	0.533

The composite scale created from Q17 (extent of team learning prioritisation) and Q12 (level of AI-driven tool adoption) yielded a Cronbach's Alpha of 0.533. This value indicates moderate internal consistency, which suggests that the items are somewhat related but may not be robustly measuring a single construct.

A linear regression analysis was performed to examine the relationship between the prioritisation of team learning (Q17) and the integration of AI-driven learning tools (Q12). The analysis resulted in a significant regression model, $F(1, 389) = 59.522$, $p < 0.01$, indicating that the extent of team learning prioritisation is a significant predictor of the level of AI tool adoption. The coefficient of determination, R^2, was 0.133, with an adjusted R^2 of 0.13, which suggests that approximately 13.3% of the variance in AI tool integration can be explained by how much the organisation prioritises team learning.

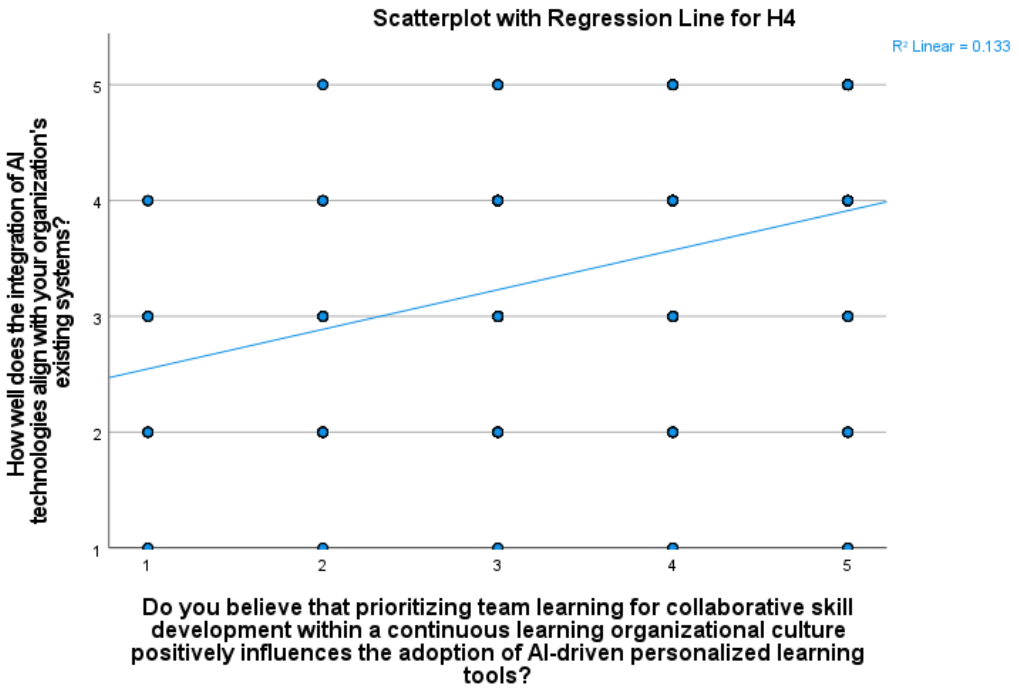

Figure 10: Scatterplot with Regression Line for H4

The scatterplot figure above demonstrates a relationship, with an R-squared value of 0.133. This value signifies a positive but moderate influence on technological integration decisions.

The regression coefficient (B = .342) was found to be significant, $t(389) = 7.715$, $p < 0.01$, indicating a positive relationship between team learning prioritisation and AI tool adoption. Table 13 below presents a full summary of the regression coefficients for the two variables.

Table 13: Regression coefficients for H4

Variable	B	95%CI	β	t	p
Constant	2.206	[1.88, 2.53]	-	13.456	<.001
Team learning prioritisation (Q17)	.342	[.26, .43]	.364	7.715	<.001

Note. Constant = 0.342, $F(1, 389) = 59.522$, $p < 0.01$, $R^2=0.13$

The positive and statistically significant regression coefficient for Q17 supports the alternative hypothesis (H4), which indicates that organisations that place a greater emphasis on team learning are indeed more likely to adopt AI-driven learning tools. The significance of the regression model allows the rejection of the null hypothesis (H0) in favour of the alternative (H4), suggesting a meaningful relationship between team-learning prioritisation and AI tool adoption within organisations. This finding highlights the importance of a collaborative learning culture in

facilitating the integration of new technologies for enhancing learning experiences. The moderate level of explained variance suggests that while team-learning prioritisation is an important factor, other variables not included in the model may also play significant roles in the adoption of AI-driven tools.

4.5.5 Hypothesis 5 (H5): Inferential Statistics

Hypothesis 5 (H5) suggests that participants who have experienced shifts in their mental models through prior learning and development programmes are more likely to engage with AI-driven personalised learning tools. The null hypothesis (H0) asserts that there is no relationship between shifts in mental models as a result of learning experiences and the engagement with AI-driven personalised learning tools.

Table 14: Reliability Statistics for H5

Independent Variable	Dependent Variable	Cronbach Alpha
Shifts in mental models (Q18)	Adoption of AI tools (Q9)	0.603

The scale combining Q18, which measured the impact of prior learning on mental models, and Q9, which assessed the intention to adopt AI-driven personalised learning tools, reported a Cronbach's Alpha of 0.603. This indicates a moderate level of internal consistency. While this alpha value is below the commonly accepted threshold of 0.7 for good reliability, it suggests that the items have a fair degree of correlation and can be tentatively considered for further analysis.

A linear regression analysis was conducted to assess the predictive power of changed mental models on the intention to adopt AI-driven personalised learning tools. The resulting model was highly significant, $F(1, 389) = 90.48$, $p < 0.01$, indicating a meaningful statistical relationship between the two variables. The R-squared value of 0.189 means that approximately 18.9% of the variance in the intention to adopt AI tools can be explained by the participants' shifts in mental models. The adjusted R-squared of 0.187 confirms that this model retains its explanatory power even after adjusting for the number of predictors.

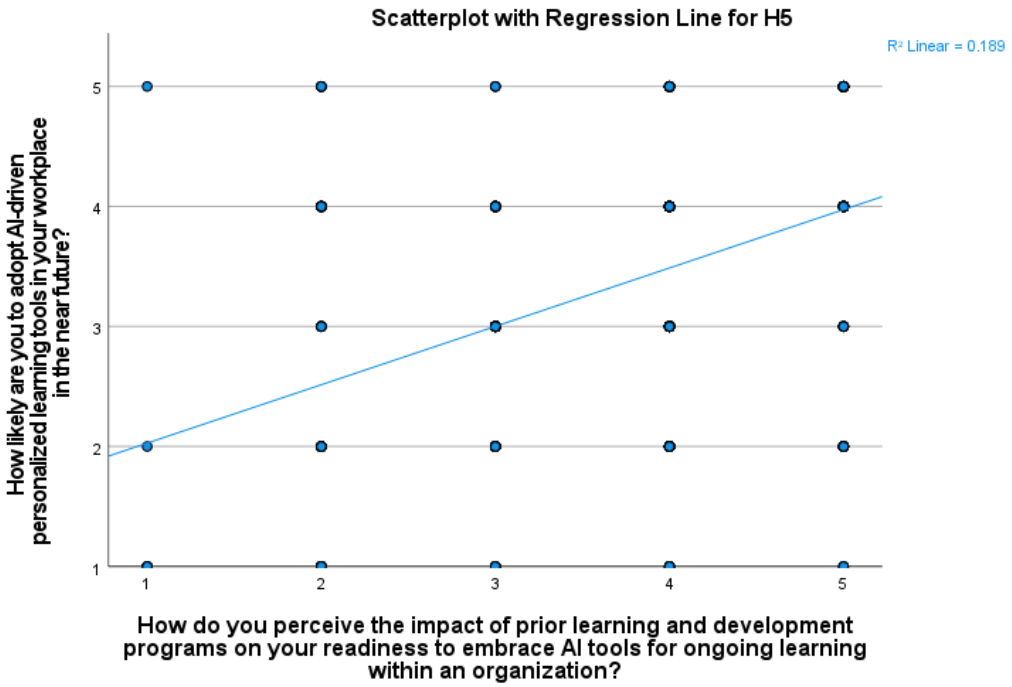

Figure 11: Scatterplot with Regression Line for H5

The scatterplot above illustrates that individuals' perception of the impact of prior learning and development programmes on their readiness to use AI tools for ongoing learning within an organisation has a positive correlation with their likelihood to adopt such tools, as reflected by an R-squared value of 0.189. This suggests that previous developmental initiatives can significantly shape future technological engagement.

The regression coefficient for Q18 (B = .486) was significant, $t(389) = 9.512$, $p < 0.01$, denoting a substantial positive relationship between the independent variable and the dependent variable. For each unit increase in the reported shift in mental models, there is an associated increase of 0.486 units in the intention to adopt AI tools. Table 15 below presents a full summary of the regression coefficients for the two variables.

Table 15: Regression Coefficients for H5

Variable	B	95%CI	β	t	p
Constant	1.524	[1.16, 1.92]	-	7.947	<.001
Shifts in mental models (Q18)	.486	[.39, .59]	.434	9.512	<.001

Note. Constant = 0.486, $F(1, 389) = 90.48$, $p < 0.01$, $R^2=0.189$

The statistical analysis provides robust support for the alternative hypothesis (H5). The significant positive regression coefficient demonstrates that changes in mental models brought about by prior learning experiences are associated with an increased intention to adopt AI-driven personalised learning tools. The null hypothesis (H0) is therefore rejected in favour of H5.

These findings underscore the importance of prior learning experiences in shaping attitudes towards new technologies and suggest that interventions aimed at altering mental models could be effective in promoting the adoption of innovative learning tools. The moderate effect size indicates that while mental model shifts are a notable factor in predicting technology adoption, other variables not included in the model may also influence this intention.

4.5.6 Hypothesis 6 (H6): Inferential Statistics

Hypothesis 6 (H6) postulates that individuals who value systems thinking are more likely to perceive AI-driven personalised learning tools as beneficial. The null hypothesis (H0), which stands as the counterclaim, argues that the valuation of systems thinking has no bearing on the perceived benefits of AI-driven learning tools.

Table 16: Reliability Statistics for H6

Independent Variable	Dependent Variable	Cronbach Alpha
Systems thinking (Q19)	Perceived AI benefits (Q6)	0.715

The Cronbach's Alpha for the scale comprising items from Q19 (the extent to which participants embrace AI tools aligned with holistic and systems thinking) and Q6 (perceived benefits of AI-enhanced learning) was found to be 0.715. This indicates a good level of internal consistency and suggests that the two items are reasonably related and together form a reliable construct, which indicates that the scale items have a sufficient correlation to justify their combined use.

A linear regression analysis was conducted to explore the relationship between the value placed on systems thinking (Q19) and the perceived benefits of AI-driven learning tools (Q6). The resulting statistical model was highly significant, $F(1, 389) = 175.258$, $p < 0.01$, indicating that systems thinking is a robust predictor of perceived AI benefits. The coefficient of determination, R^2, was 0.311, and the adjusted R^2 was 0.309, which illustrates that approximately 31.1% of the variance in the perceived benefits of AI-enhanced learning is explained by systems thinking. This is a substantial amount and suggests that systems thinking is a major factor in how individuals evaluate AI tools for learning.



Figure 12: Scatterplot with Regression Line for H6

The scatterplot above displays a positive linear relationship between participants' positive attitude to AI-driven learning tools that align with systems thinking principles and their belief in AI's capacity to enhance personalised learning experiences. The relationship highlights the substantial influence of a systems thinking approach on the adoption of AI in learning and development.

The regression coefficient (B = .578) was found show a statistically significant positive relationship, t(389) = 13.239, p < 0.01, which implies that as the value placed on systems thinking increases, so does the perceived benefit of AI-driven learning tools. Table 17 below presents a full summary of the regression coefficients for the two variables.

Table 17: Regression Coefficients for H6

Variable	B	95%CI	β	t	p
Constant	1.347	[1.01, 1.68]	-	7.877	<.001
Systems thinking (Q19)	.578	[.49, .66]	.557	13.239	<.001

Note. Constant = 0.578, F(1, 389) = 175.258, p < 0.01, R^2=0.311

The positive and statistically significant outcomes of the regression analysis strongly support the alternative hypothesis (H6). The findings indicate that individuals who incorporate systems

thinking into their approach are more likely to perceive AI-driven personalised learning tools as beneficial. The magnitude of the regression coefficient and the significance level allow the null hypothesis (H0) to be rejected in favour of H6, affirming the predictive power of systems thinking concerning positive perceptions of AI in learning.

These results underscore the influence of cognitive frameworks, such as systems thinking, on the reception and evaluation of technological tools in educational contexts. They highlight the potential for leveraging systems thinking to foster more favourable perceptions and higher adoption rates of AI-driven learning innovations.

4.5.7 Hypothesis 7 (H7): Inferential Statistics

Hypothesis 7 (H7) posits that a supportive regulatory environment that fosters technological innovation and adoption will positively influence attitudes toward AI-driven personalised learning tools. The null hypothesis (H0) contends that there is no relationship between a supportive regulatory environment and positive attitudes towards AI-driven personalised learning tools.

Table 18: Reliability Statistics for H7

Independent Variable	Dependent Variable	Cronbach Alpha
Regulatory support (Q20)	Perceived AI benefits (Q6)	0.659

The internal consistency of the scale, as measured by Cronbach's Alpha, combining responses from Q20 (supportive regulatory environment) and Q6 (perceived benefits of AI-enhanced learning), was found to be 0.659. This alpha value is indicative of a moderate level of reliability, which suggests that while the items are related, the scale could benefit from further refinement to strengthen its internal consistency.

The linear regression model used to examine the relationship between the perceived supportiveness of the regulatory environment (Q20) and the perceived benefits of AI-enhanced learning (Q6) was statistically significant, $F(1, 389) = 124.305$, $p < 0.01$. This indicates that the regulatory environment is a predictor of the perceived benefits of AI in learning.

The coefficient of determination, R^2, was 0.242, with an adjusted R^2 of 0.240, which means that approximately 24.2% of the variance in perceived benefits of AI-enhanced learning can be explained by the perceived regulatory support.

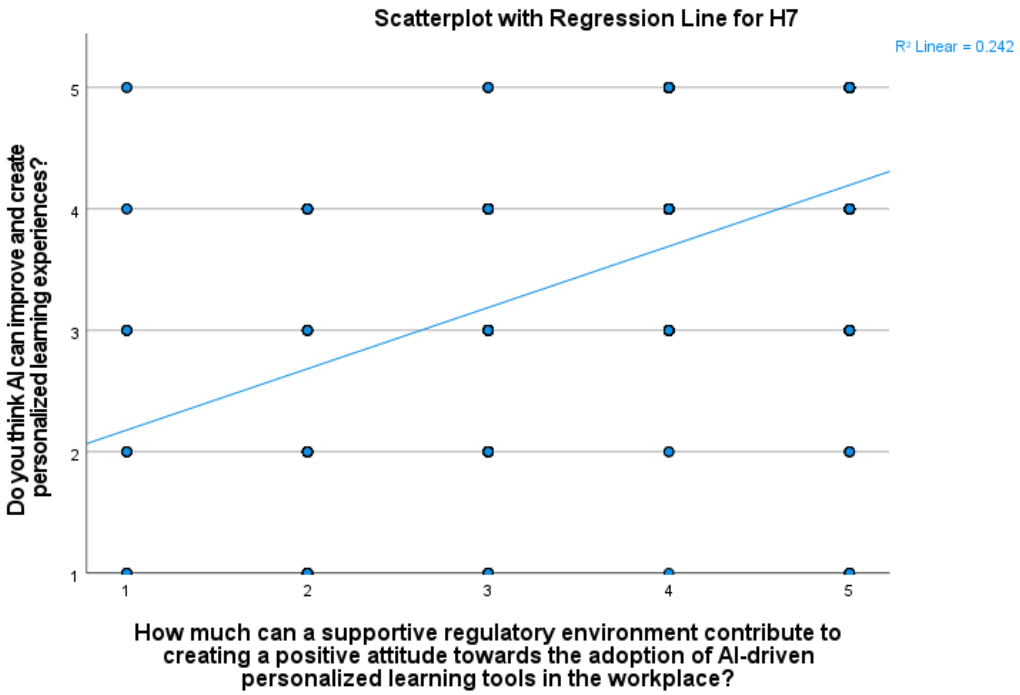

Figure 13: Scatterplot with Regression Line for H7

The scatterplot figure above indicates a notable linear correlation, as reflected by an R-squared value of 0.242. This indicates the significant role that regulatory frameworks play in the acceptance and endorsement of AI in educational settings.

The regression coefficient (B = .504) was significant, t(389) = 11.149, p < 0.01, indicating a positive relationship between the variables. Table 19 below presents a full summary of the regression coefficients for the two variables.

Table 19: Regression Coefficients for H7

Variable	B	95%CI	β	t	p
Constant	1.674	[1.33, 2.1]	-	9.675	<.001
Regulatory support (Q20)	.504	[.42, .59]	.492	11.149	<.001

Note. Constant = 0.504, F(1, 389) = 124.305, p < 0.01, R^2=0.24

The positive and statistically significant regression coefficient for Q20 confirms that the alternative hypothesis (H7) is supported. The findings suggest that individuals who perceive a regulatory environment as supportive of technological innovation are more likely to recognise the benefits of AI-enhanced learning tools. Consequently, the null hypothesis (H0) is rejected in favour of the alternative hypothesis.

These results point to the importance of regulatory support in shaping positive attitudes toward AI-driven learning innovations. The significant portion of the variance explained by the model suggests that regulatory factors play a substantial role in influencing how AI tools are perceived in the context of learning and development.

4.5.8 Hypothesis 8 (H8): Inferential Statistics

Hypothesis 8 (H8) proposes that competitive pressures driving organisations to adopt innovative technologies will positively impact employees' attitudes toward AI-driven personalised learning tools. Accordingly, the null hypothesis (H0) maintains that competitive pressures have no significant effect on employees' attitudes towards these technologies.

Table 20: Reliability Statistics for H8

Independent Variable	Dependent Variable	Cronbach Alpha
Competitive pressures (Q21)	Perceived effectiveness of AI (Q14)	0.643

The reliability of the combined scale, which includes items from Q21 (perception of competitive pressures) and Q14 (perceived effectiveness of AI-driven personalised learning), was determined by a Cronbach's Alpha of 0.643. This indicates a moderate level of internal consistency; it suggests that the items have a reasonable degree of correlation and may represent a cohesive construct.

The linear regression analysis aimed to evaluate the influence of competitive pressures (Q21) on the perceived effectiveness of AI-driven personalised learning (Q14). The model was found to be highly significant, $F(1, 389) = 113.171$, $p < 0.01$, indicating a substantial relationship between the two variables. The coefficient of determination (R^2) was 0.225, with an adjusted R^2 of 0.223, suggesting that about 22.5% of the variance in the perceived effectiveness of AI-driven personalised learning can be attributed to competitive pressures.

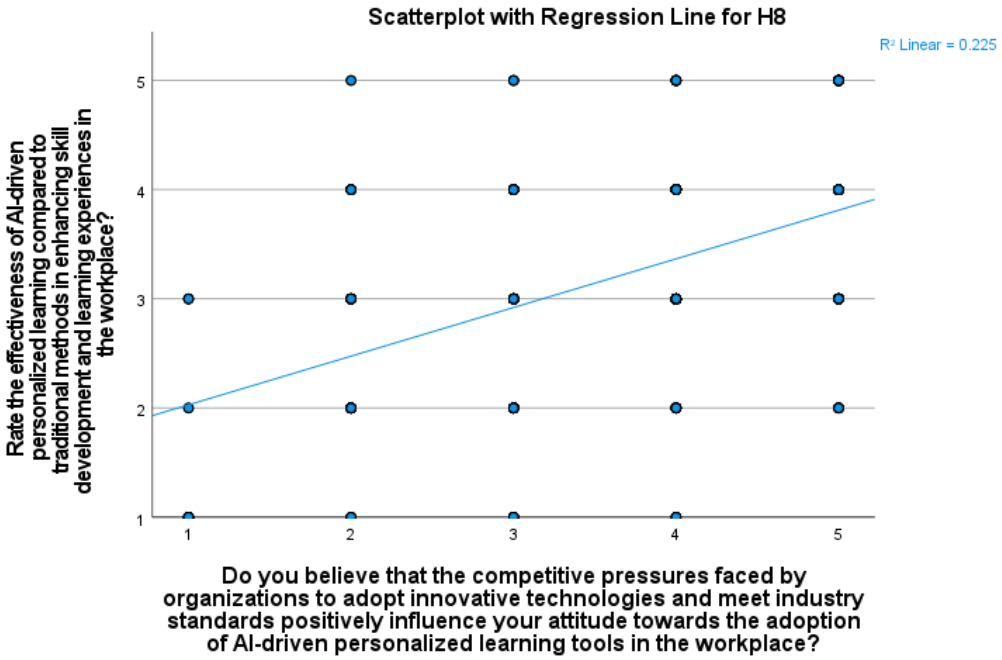

Figure 14: Scatterplot with Regression Line for H8

The scatterplot depicts a positive linear relationship, which suggests that the pressure to innovate and meet standards is a considerable factor in the valuation of AI technologies for enhancing learning and development within the workplace.

The regression coefficient (B = .446) was found to be significant, t(389) = 10.638, p < 0.01, reflecting a positive relationship between competitive pressures and the perceived effectiveness of AI learning tools. Table 21 below presents a full summary of the regression coefficients for the two variables.

Table 21: Regression Coefficients for H8

Variable	B	95%CI	β	t	p
Constant	1.584	[1.27, 1.9]	-	9.94	<.001
Competitive pressures (Q21)	.446	[.36, .53]	.475	10.638	<.001

Note. Constant = 0.446, F(1, 389) = 113.171, p < 0.01, R^2=0.225

The statistically significant positive regression coefficient achieved for Q21 supports the alternative hypothesis (H8), which indicates that the more employees perceive competitive pressures to adopt new technologies, the more likely they are to view AI-driven personalised learning tools as effective. This conclusion leads to the rejection of the null hypothesis (H0) and

acceptance of H8, affirming the role of competitive pressures in shaping positive attitudes towards AI in learning and development. These results highlight the importance of industry competition as a driver of the acceptance and perceived value of innovative learning tools among employees. The relative strength of the model, as indicated by the R-squared value, points to competitive pressures as a notable factor that influences employee attitudes toward technology in the workplace.

4.5.9 Summary of hypotheses findings

The investigation into the influence of various factors on the adoption and perception of AI-driven personalised learning tools in the workplace has led to insightful findings. The regression analyses provided robust evidence for each hypothesis, with significant p-values indicating strong support for the predicted relationships. Table 22 below provides a summary of the outcomes for each hypothesis tested, offering a concise overview of the results.

Table 22: Summary of Hypotheses Outcomes

Hypothesis	Independent Variable	Dependent Variable	Outcome	Significance	Notes
H1	Familiarity with AI	Learning Tools	Supported	$p < 0.01$	**R**elative advantage of AI familiarity correlated positively with the use of new AI learning tools.
H2	Compatibility with AI	Intention to adopt	Supported	$p < 0.01$	**C**ompatibility perceptions predicted intention to adopt AI tools.
H3	Alignment with personal vision	Intention to adopt	Supported	$p < 0.01$	**S**trong alignment with personal learning visions led to greater engagement.
H4	Team-learning prioritisation	integration of AI	Supported	$p < 0.01$	**O**rganisations that prioritise team learning are more inclined to adopt AI tools.
H5	Shifts in mental models	Adoption of AI tools	Supported	$p < 0.01$	**C**hanges in mental models caused by learning experiences are linked to increased adoption.
H6	Systems thinking	Perceived AI benefits	Supported	$p < 0.01$	**A** systems thinking approach is associated with higher perceived benefits of AI.
H7	Regulatory support	Perceived AI benefits	Supported	$p < 0.01$	**R**egulatory support influences the perceived benefits of AI in learning.

H8	Competitive pressures	Perceived effectiveness of AI	Supported	$p < 0.01$	**C**ompetitive pressures positively influence perceptions of AI effectiveness.

4.6 Conclusion

The presentation of results in this chapter revealed insightful findings on the perception of AI in workplace learning, engagement in self-directed learning, and AI implementation within organisations. The descriptive statistics provided a snapshot of the current state of AI-driven personalised learning initiatives, highlighting a moderate level of familiarity and adoption among participants. The regression analysis offered a deeper understanding of the factors influencing these initiatives, confirming several of the hypotheses proposed based on the TOE framework and Learning Organisation theory.

These findings suggest that while there is an acknowledgment of the potential benefits of AI in personalising learning experiences, there are also some challenges and concerns that need to be addressed to fully leverage AI's capabilities. The analysis of engagement in self-directed learning emphasised the critical role of individual motivation and organisational support in the effective use of AI tools. Furthermore, the examination of AI implementation highlighted the importance of both internal and external factors in facilitating or hindering the adoption of AI solutions. The results chapter successfully bridged the gap between theoretical expectations and empirical reality, providing a nuanced understanding of the interplay between AI technology and personalised learning in the workplace.

Chapter 5: Discussion

The previous chapters laid the groundwork for understanding the potential of AI for personalised learning in the workplace. This chapter synthesises the research findings with the extant literature to engage in a critical discourse on the implications of AI-driven personalised learning within the context of continuous learning organisations.

5.1 Perception of Artificial Intelligence in Workplace Learning

The results of this study demonstrate a moderately positive perception of AI in workplace learning among employees. This perception is characterised by a general familiarity with AI technologies, a recognition of the potential benefits of AI in enhancing learning experiences and a relatively low level of concern regarding AI implementation.

The moderate level of employee familiarity with AI technologies (Mean = 3.06) suggests an emerging awareness of AI's role in workplace learning. This indicates that while employees are beginning to understand AI's potential, there is still a need for increased training and exposure to enhance their comfort and proficiency with these technologies. The survey revealed an above-neutral familiarity with AI technologies among employees, which aligns with the observations made by Vincent-Lancrin and van der Vlies (2020) and Pillai et al. (2023). These studies emphasise the increasing integration of AI into various sectors, including education and HR, which is likely to contribute to this familiarity. This level of familiarity suggests a growing exposure to AI technologies in the workplace, potentially influenced by the recent surge in digital transformation strategies across industries to deliver operational efficiencies, as noted by Nam et al. (2021).

The results also indicate a recognition of the benefits of AI in personalising learning experiences (Mean = 3.51), aligning with literature that positions AI as a transformative force in education and professional development (Farmiloe, 2023; Kolog et al., 2022; Weinstein et al., 2019). Employees acknowledged the benefits of AI in creating personalised learning experiences. This is consistent with the views of Hashim et al. (2022), who argue that AI's capability to tailor learning experiences to individual needs is one of its most important advantages. Crompton and Burke's (2023) systematic review of AI in higher education underscores the recognition of AI's potential benefits in enhancing learning experiences, highlighting the value that AI can add in terms of efficiency and effectiveness. Similarly, Yim and Su's (2024) investigation into AI learning tools in K-12 education emphasises the personalisation that AI brings to the learning processes.

The comparatively low levels of concern about AI implementation (Mean = 2.52) may reflect an underlying trust in organisational strategies for handling AI integration ethically and inclusively, resonating with the ethical considerations advocated by Weinstein et al. (2019). This trust is critical for the adoption of AI technologies as it suggests a workforce that is ready to engage with new tools, provided there is clear communication and support from their organisation. Lukyanenko et al. (2022) Foundational Trust framework underscores the importance of trust for the adoption of AI technologies, with trust promoting a workforce readiness to engage with new tools. This readiness by employees is contingent upon clear communication and support from their organisation, a sentiment echoed in Wong et al. (2023) exploration of the institutional role and the role of self in the formation of trust in AI technologies. This reduced concern may also reflect a growing acceptance and normalisation of AI as a tool in workplace learning, potentially the result of the ongoing dialogues and initiatives aimed at demystifying AI and addressing common misconceptions and fears.

The interpretation of these results indicates a workforce in transition, gradually moving toward a deeper engagement with AI as a tool for personalised learning. The positive perception of AI's potential benefits suggests a workforce that is, at least theoretically, ready to embrace AI if provided with the right support and information. This readiness is an asset for organisations that aim to implement AI in their learning ecosystems. Moreover, the low levels of concern may reflect confidence in organisational strategies for ethical AI integration. However, this confidence must not lead to complacency; organisations must actively work to maintain trust by ensuring transparency and addressing the potential implications of AI for job security and privacy, as noted by Reinhardt (2023). While the fact that the study reveals a positive perception of AI in workplace learning is encouraging, it is important to maintain a balanced view. Concerns regarding data privacy, job displacement and over-reliance on technology for learning processes should be carefully considered and addressed (Georgieff & Hyee, 2022; Gwagwa et al., 2020). A critical counterargument to the perceived usefulness of AI is the potential for AI to perpetuate biases, an issue highlighted by researchers in AI ethics. Addressing this issue requires a commitment to developing and using AI in a way that is fair, transparent and inclusive, as noted by Tallberg et al. (2023). Another consideration is the digital divide. Ensuring equitable access to AI-driven learning resources is essential to prevent widening the gap between those with and without access to these technologies, as noted by Nguyen et al. (2023).

In conclusion, the perception of AI in workplace learning is generally positive, with a recognition of its potential benefits and a relatively low level of concern about its implementation. This perception is shaped by a growing familiarity with AI technologies, influenced by their increasing

presence in the modern workplace. However, a balanced approach that addresses potential concerns and ethical considerations is essential for the successful integration of AI into workplace learning strategies. The results offer valuable insights for organisations that are looking to harness the power of AI in learning and development while navigating its challenges responsibly.

5.2 Engagement in Self-Directed Learning

The results indicated a moderately high level of engagement in self-directed learning activities among employees. This is paralleled by a moderate level of adoption of AI-driven personalised learning tools and a strong perception of the importance of self-directed learning for skills development in the workplace.

The survey's findings on self-directed learning, reflecting a moderate to high level of engagement (Mean = 3.50), indicate that contemporary employees are increasingly taking charge of their learning trajectories, as described by Budhiraja (2023). This proactive approach to professional development is in line with the agility required in modern workplaces, where continuous learning is a cornerstone of competitiveness. This engagement could be attributed to the evolving workplace dynamics, where individuals are increasingly recognising the necessity for continuous skill enhancement, a trend accelerated by the digital transformation of many industries, as noted by Smith (2020).

Furthermore, the moderate adoption of AI-driven personalised learning tools (Mean = 3.31) aligns with the recognition by Smith (2020) that while organisations are strategically addressing learning needs, employees still face challenges in dedicating time to learning amidst other work demands. The moderate adoption rate of AI-driven tools suggests an emerging trend but also points to possible barriers or hesitance in fully embracing these technologies. This aligns with the observations of Shemshack and Spector (2020), who note that while AI offers significant advantages in personalised learning, its integration necessitates continuous research and collaboration to maximise its potential in education and the workplace. The variance in the rate of adoption among participants suggests differing levels of AI readiness across organisations, which could be influenced by factors such as organisational culture, technological infrastructure and leadership support.

The high value placed on self-directed learning for skills development (Mean = 3.71) suggests that employees are aware of the importance of continuous learning, echoing the findings of Kolog et al. (2022), which emphasise the role of personalised learning in fostering a culture of continuous

professional growth. The high rating of the importance of self-directed learning for skills development affirms the views of Poquet and Laat (2021) and Harry (2023), who emphasise the role of technology in enabling personalised learning paths and empowering learners. This perception indicates a growing awareness among employees about the significance of self-directed learning in staying relevant and competitive in the rapidly evolving job market.

The results suggest a workforce that is increasingly autonomous, motivated and equipped to steer its professional development, a sign of the evolving dynamics of workplace learning where digital tools become facilitators rather than directors of growth. This shift towards self-directed learning reflects a deeper trend of employee empowerment and the desire for personalisation in professional development, as noted by Lemmetty and Collin (2020). While the trend towards self-directed learning is evident, counterarguments suggest that not all employees may be equally prepared or inclined to adopt this mode of learning, as noted by Silamut and Sovajassatakul (2021). Resistance to self-directed learning may stem from a variety of factors, including discomfort with technology, lack of time or a preference for more structured learning environments.

In summary, the engagement in self-directed learning activities reflects a growing trend towards continuous professional development, supported by a moderate adoption of AI-driven personalised learning tools. This highlights a recognition of the importance of self-learning in the evolving work environment. However, to leverage the potential of AI fully in facilitating self-directed learning, organisations need to create supportive cultures, address barriers to technology adoption and ensure equitable access to learning resources. The results underscore the need for a balanced approach that combines the advantages of AI with the diverse learning needs and preferences of employees.

5.3 Artificial Intelligence Implementation

The survey results revealed varying perceptions of AI implementation factors, with moderate scores for technological and organisational factors and a higher score for environmental factors.

The survey data on AI implementation reflects a nuanced picture that parallels the literature on the integration of technology within organisations. Specifically, the moderate technological readiness (Mean = 3.17) suggests that while foundational AI infrastructure exists, there may be gaps in advanced technological capabilities or user training that need to be addressed to fully leverage AI's potential. The moderate level of technological readiness (Mean = 3.17) aligns with

the observations by Kitsios and Kamariotou (2021) on the evolving inclusion of AI in business processes. The moderate perception of technological readiness aligns also with Bader and Kaiser's (2019) observation regarding the challenges and concerns surrounding the loss of control and unintended consequences in AI adoption. This suggests a cautious approach to AI integration, possibly brought about by apprehensions about the complexity and compatibility of AI systems within existing infrastructures, as explored by Wilkens (2020).

The slightly more favourable view of organisational factors (Mean = 3.41) supports the findings of Jarrahi et al. (2023), which suggest that organisations are increasingly recognising the value of AI in optimising employee development. The slightly higher perception of organisational readiness for AI also correlates with the findings of Kitsios and Kamariotou (2021), who emphasise the significant impact of AI on enhancing business value and stakeholder engagement. Organisations seem to be gradually recognising the importance of internal support structures and processes that facilitate AI integration, reflecting a growing acknowledgement of AI's potential in organisational learning and performance enhancement.

Finally, the recognition of environmental factors (Mean = 3.67) resonates with the broader context described by Neumann et al. (2022), where market dynamics, competitive pressures and regulatory frameworks are crucial for technology adoption. The high score for environmental factors suggests a recognition of the favourable external conditions for AI adoption within the industry, as also indicated by the works of Stenberg and Nilsson (2020). This implies that external market dynamics, regulatory support and industry trends are perceived as conducive to AI adoption, echoing the role of external factors in shaping innovation (Neumann et al., 2022; Stenberg & Nilsson, 2020).

The positive correlation found between technological readiness and organisational support for AI initiatives ($r = .549$, $p < .01$) aligns with the findings of authors such as Gangwar et al. (2015), who looked at the potential for cloud computing to integrate smoothly with an organisation's architecture and data formats. This correlation indicates that as organisations enhance their technological capabilities, they concurrently develop supportive structures and processes. The relationship between technological capabilities and supportive structures is pivotal as it implies that technological advancement and organisational adaptability are interconnected in the successful implementation of AI in learning environments. Conversely, the non-significant correlation between technological and environmental factors ($r = -.022$, $p > .05$), as well as between organisational and environmental factors, suggests a complex dynamic. This result indicates that while internal company strategies and capabilities are seen as crucial, the influence

of the external environment, including market trends and regulatory frameworks, is not directly perceived as having an impact on AI implementation. This finding resonates with the perspectives of authors such as Srivastava et al. (2022), who note that while external factors are influential, internal organisational dynamics often play a more immediate role in technology adoption decisions.

The findings suggest that while organisations are technologically gearing up for AI implementation, the variation in readiness indicates differing levels of preparation and resource allocation. Organisational factors scored slightly higher, suggesting that many workplaces are beginning to put the necessary support structures in place for AI integration. The recognition of environmental factors as the most influential suggests that external pressures and incentives are significant motivators for AI adoption. While the data presents a positive outlook on AI implementation, a balanced perspective must consider the potential challenges and resistance within organisations. Counterarguments suggest that despite technological readiness, cultural resistance or a lack of strategic vision may impede effective AI adoption, as highlighted by Ade-Ibijola and Okonkwo's (2023) study on the challenges facing the adoption of AI technologies in Africa. Moreover, the complexities of ethical AI integration and the potential for job displacement could contribute to hesitancy within the workforce (Ade-Ibijola & Okonkwo, 2023; Bankins & Formosa, 2023).

The results indicate a moderate to high perception of the relevance of AI implementation factors across the technological, organisational and environmental dimensions. To harness the potential of AI in the workplace effectively, organisations need to focus on improving technological readiness, strengthening organisational support structures and leveraging favourable external conditions. While the external environment appears to be conducive to AI adoption, addressing internal barriers and ethical considerations is crucial for successful and responsible AI integration. The findings highlight the need for a balanced and strategic approach to AI implementation, considering both internal capabilities and external influences.

5.4 Discussion pertaining to Hypotheses 1–8

5.4.1 Hypothesis 1 (H1): Discussion

The analysis of Hypothesis 1 (H1) revealed a strong positive relationship between employees' perceived relative advantage of AI in self-directed learning and the effectiveness of AI-driven personalised learning over traditional methods. The survey results related to H1 mirror the optimism present in the literature regarding AI's potential in the workplace, such as de Laat et al.

(2020) notes on AI's transformative impact on training and professional development, and Kolog et al. (2022) findings on AI's role in customising learning content to individual needs.

The survey results indicated that as familiarity with AI technologies increases, concerns about AI implementation decrease. This finding suggests that educational initiatives focused on increasing AI literacy can significantly reduce apprehensions about AI, fostering a more supportive environment for its adoption in workplace learning. This negative correlation ($r = -1.64$, $p < .01$) aligns with prior research by Nam et al. (2021), who found that familiarity with AI positively impacts its perceived utility and decreases any apprehension about using it. The positive linear relationship found between the belief in AI's potential to enhance personalised learning experiences and its perceived effectiveness suggests a strong cognitive alignment. Participants who recognised AI's advantages tended to view AI-driven learning as more effective. This notion also highlighted by Stenberg and Nilsson (2020). Furthermore, the regression model explained a significant portion ($R^2 = 0.444$) of the variability in the perceived effectiveness of AI-driven personalised learning, underlining the influential role of AI familiarity and perceived benefits. Shemshack and Spector (2020) discuss a similar notion, highlighting the evolving nature of personalised learning as a result of rapid technological advancements.

The findings corroborate the idea that perceptions of technological advancements significantly influence their acceptance and effectiveness in workplace learning, as suggested in the TOE framework by Depietro et al. (1990). Employees who perceive AI as a beneficial tool for personalised learning are more likely to rate its effectiveness highly, which is consistent with theories of technology acceptance and innovation diffusion (Rogers et al., 2014). The high correlation supports the views of Nam et al. (2021) and Stenberg and Nilsson (2020), who emphasise that recognising AI's advantages, such as customisation and efficiency, is crucial for adoption. The substantial proportion of variance explained by this relationship (44.4%) suggests that employees who are aware of the potential benefits of AI, such as tailored learning experiences and increased engagement, are more likely to perceive AI-driven learning tools as effective. This may be because of an understanding that AI can offer more personalised, efficient and data-driven learning solutions compared to traditional methods, as noted by Kelley (2022).

The effective integration of AI into learning environments necessitates a comprehensive understanding of the workforce's diverse experiences with technology, including varying levels of digital literacy and potential resistance owing to fears of becoming obsolete. Tapalova and Zhiyenbayeva (2022) emphasise the need for caution regarding AI's tendency to standardise learning, potentially overshadowing human-centred pedagogical methods. Kelley (2022) supports

this viewpoint, advocating that AI is seen as a supplementary tool rather than as a replacement for traditional, adaptable learning methodologies. While AI's relative advantage is clear, it is essential to acknowledge its potential limitations and important to recognise that perceived benefits do not automatically lead to smooth adoption or effective implementation. Moreover, the perception of AI's effectiveness does not necessarily correlate with user satisfaction or acceptance. Chou et al. (2022) point out that factors such as information and communication technology (ICT) self-efficacy and human-computer interaction experience play significant roles in determining the success of AI-based technology applications. Resistance to technological change is a major hurdle in the successful implementation and acceptance of these technologies. For this reason, while AI presents promising opportunities in education, addressing these challenges is essential for its successful incorporation into learning environments.

The strong correlation between the perceived relative advantage of AI in self-directed learning and its effectiveness underscores the importance of recognising AI's benefits in workplace learning. Organisations should focus on highlighting AI's unique advantages, addressing potential concerns and ensuring equitable access to these technologies. While the advantages of AI in personalised learning are evident, a balanced approach that considers both the opportunities and challenges of AI implementation is essential for its successful integration into workplace learning strategies.

5.4.2 Hypothesis 2 (H2): Discussion

Hypothesis 2 (H2) was used to explore the notion that a perceived strong compatibility between AI-driven personalised learning tools and existing workplace structures would positively influence employees' intentions to adopt these tools. The analysis provided substantial support for this hypothesis. The findings point to the significance of technological integration within organisational structures for effective AI adoption. This resonates with the literature reviewed and mirrors insights from Stenberg and Nilsson (2020) and Tongsuksai et al. (2023), which emphasise the importance of fitting new technologies into existing organisational contexts.

The regression analysis indicated a strong positive relationship between the perceived compatibility of AI-driven tools with the workplace and employees' intention to adopt them. This finding is aligned with the TOE framework by Depietro et al. (1990), which stresses the importance of compatibility in technology-adoption decisions. The correlation coefficient ($r = .549$, $p < .01$) between technological and organisational factors supports the argument that advancements in AI technology are more readily adopted when they align with existing organisational structures and

processes. This point is underscored by Gangwar et al. (2015) in their study on integrating cloud computing smoothly with an organisation's architecture and data formats. The significant regression model ($F(1, 389) = 247.58$, $p < 0.001$) with a substantial R-squared value (0.389) highlights the pivotal role of compatibility in the adoption of AI-driven learning tools, resonating with the findings of Srivastava et al. (2022) regarding the adoption of Industry 4.0 technologies in educational institutions. Finally, the survey results indicated a strong positive correlation between the perceived compatibility of AI-driven personalised learning tools with existing workplace structures and employees' intentions to adopt these tools ($R^2 = 0.389$). This suggests that when employees perceive AI tools as congruent with their current working environment, they are more inclined to adopt them.

The positive correlation resonates with the findings of Hashim et al. (2022), which point to the significance of integrating AI tools into the organisational learning environment. When these tools are perceived as compatible with current workplace structures and culture, they are more readily accepted and used by employees. These findings are consistent with the literature that highlights the role of organisational factors in the effective integration of AI into the workplace (Weinstein et al., 2019). Such literature suggests that for AI-driven personalised learning tools to be effectively adopted, they must be not only technologically advanced but also compatible with the existing work culture and structure. The substantial proportion of the variance (38.9%) explained by this relationship in the current study indicates that the integration of AI tools within the existing organisational framework is a crucial factor in determining their adoption. Employees are more likely to embrace AI-driven learning tools when they see them as fitting seamlessly into their current work practices and processes, as noted by Ng et al. (2023). This indicates a preference for technologies that do not disrupt established routines but rather enhance and streamline existing workflows.

In reflecting on these results, employees might initially perceive AI tools as compatible, but practical challenges may emerge during actual usage. This highlights the importance of continuous evaluation and adjustment of AI tools post-implementation. Moreover, focusing solely on compatibility may lead to overlooking other crucial factors such as the quality of content, ease of use and the actual effectiveness of the AI tool in enhancing learning outcomes (D'Mello, 2021). It is essential to maintain a balance between ensuring compatibility and addressing these other critical aspects of AI tool effectiveness. While the positive correlation is insightful, it is important to recognise that compatibility alone does not ensure successful adoption. According to Khaw et al. (2023), the implementation of congruent AI tool technologies may encounter resistance. This

resistance can be attributed to various factors such as the prevailing organisational culture, the attitudes of employees towards change and a lack of perceived necessity for the new technology.

In conclusion, supporting H2 indicates a clear link between compatibility and intention to adopt AI in workplace learning. However, for a successful and sustainable adoption, it is crucial to consider a broader range of factors, including ongoing support, adaptability and the overall quality of the AI learning experience.

5.4.3 Hypothesis 3 (H3): Discussion

Hypothesis 3 (H3) posits that individuals who perceive a strong alignment between their personal visions for skill improvement and AI-driven personalised learning tools are more likely to embrace these tools for continuous learning. The results significantly supported this hypothesis. Studies such as Al-Dhuwaihi et al. (2020) and Hutasuhut et al. (2021) support the idea that personal mastery, including the development of individual competencies and skills, is a significant factor in motivating employees to adopt new technologies such as AI for their learning. This concept is further supported by Kolog et al. (2022), who highlight the effectiveness of AI in personalising learning experiences based on individual preferences and needs.

The statistical analysis revealed a positive relationship between the perceived alignment of AI-driven learning tools with individual professional development goals and the intention to adopt these tools (regression coefficient $B = .328$, $p < 0.01$). This underscores the importance of aligning AI learning initiatives with employees' career aspirations to enhance their adoption and effectiveness. Organisations should tailor AI-driven learning tools to meet individual development goals, thereby increasing employee engagement and satisfaction. This outcome resonates with the concept of personal mastery as detailed by Senge (2006), which emphasises the importance of aligning individual learning goals with organisational resources. The results mirror the premise that personal mastery is achieved when individuals can connect their personal goals and aspirations to the tools and opportunities provided by their organisations. The correlation between personal vision alignment and the adoption of AI tools ($R^2 = 0.082$) indicates that while personal relevance is significant, other factors also play a role in the decision to adopt AI-driven learning tools. Finally, the results indicate that when employees perceive that AI tools support their personal skill development, they are more inclined to use them.

The importance of aligning AI-driven learning tools with individual learning objectives suggests the need for a learner-centric approach in AI application in the workplace. This approach is in line

with the findings of Hutasuhut et al. (2021), which highlight the role of individual learning in organisational learning environments. The results suggest that AI-driven tools need to be perceived not merely as technological interventions but also as enablers of personal and professional growth. This interpretation is in line with the argument by Hoe (2019) regarding the importance of addressing digital competency gaps at all levels in an organisation. These findings highlight the crucial aspect of AI adoption in learning that these technologies need to be integrated into the personal learning journeys and professional aspirations of employees, as suggested by scholars such as Marik (2022) and NG (2020). Such integration increases the relevance and usefulness of AI-driven learning tools, in this way increasing their adoption and effectiveness. Although the variance explained by this relationship is relatively modest (8.2%), it suggests that personal relevance plays a role in employees' decisions to engage with AI tools. Employees are more likely to adopt AI-driven learning solutions if they see a direct connection between the tool and their personal learning objectives or career aspirations (Lemmetty & Billet, 2023; Seo et al., 2021).

Some reflective insights consider the complexity of balancing individual learning needs with organisational objectives. While personalising AI tools can enhance their adoption, it may lead to a fragmented learning strategy that does not align with the overarching organisational goals, as put forward by Seo et al. (2021). Thus, a nuanced approach is needed, one that integrates individual learning aspirations with the organisation's broader skill-development objectives. While these findings are important, it is crucial to address potential counterarguments. One could argue that personal development goals are constantly evolving. Given the dynamic nature of these goals, maintaining a consistent alignment with AI tools presents a considerable challenge, a topic explored in depth by Yim and Su (2024) in their work on AI learning tools in K-12 education. Furthermore, the modest R^2 value suggests that other factors such as organisational culture and external incentives, as explored by Liu and Liu (2022) in their work on the impact of incentives on job performance, may strongly influence the adoption of AI learning tools.

In summary, supporting H3 highlights the importance of aligning AI-driven learning tools with individual professional development goals. However, the success of such initiatives also depends on a careful balance between personalisation and alignment with the organisation's strategic learning objectives, coupled with an understanding of the dynamic nature of individual learning goals.

5.4.4 Hypothesis 4 (H4): Discussion

Hypothesis 4 (H4) was used to investigate the relationship between the prioritisation of team learning within an organisation and the integration of AI-driven personalised learning tools. The hypothesis was significantly supported, indicating that organisations that prioritise team learning are more inclined to adopt these tools. Hypothesis 4's validation resonates with the concepts articulated by Senge (2006) in his Five Disciplines of a Learning Organisation, particularly the discipline of team learning. The finding also correlates with the arguments of Hutasuhut et al. (2021) and Al-Dhuwaihi et al. (2020), who highlight the importance of collaborative learning environments for enhancing organisational performance and the adoption of new technologies, including AI.

The statistical analysis presented a significant positive relationship ($B = .342$, $p < 0.01$), with approximately 13.3% of the variance in AI tool adoption being explained by the extent of team-learning prioritisation. This finding aligns with Senge's (2006) Learning Organisation theory, particularly the concept of team learning. The finding suggests that a collaborative learning culture within an organisation enhances the integration of AI-driven learning tools. The results indicate that in environments where team learning is a priority, there is a greater openness and willingness to embrace innovative learning technologies such as AI. A significant positive correlation was shown between the prioritisation of team learning within an organisation and the integration of AI technologies ($R^2 = 0.133$). This suggests that organisations that foster a culture of collaborative learning are more inclined to adopt AI-driven personalised learning tools.

Team learning, as a component of organisational culture, plays a critical role in facilitating the adoption of AI-driven learning tools. This view aligns with the studies by Hutasuhut et al. (2021) and Marik (2022), which highlight the importance of collaborative learning and knowledge exchange in organisational growth. The emphasis on team learning suggests that AI-driven tools are more likely to be adopted in environments where knowledge sharing and collective learning are valued. This interpretation resonates with Al-Dhuwaihi et al. (2020), who emphasise the effectiveness of group learning in promoting positive relationships and enhancing teaching techniques. Organisations with a strong focus on team learning are likely to see AI tools as facilitators of collective knowledge building and problem-solving, as supported by the principles of Senge's team learning. This perspective is consistent with the emphasis on collaborative learning environments in fostering innovation and technological adoption. The R^2 value indicates that approximately 13.3% of the variance in the adoption of AI-driven tools is explained by the

extent of team learning prioritisation. This highlights the impact of a collaborative learning culture on the adoption of innovative learning technologies.

These results also acknowledge the complexity of integrating team learning within diverse organisational structures. In some settings, emphasising team learning may conflict with established norms or operational priorities. Furthermore, the effective integration of AI tools into team-learning initiatives requires careful planning, resource allocation and potentially pronounced shifts in organisational culture, as highlighted by Kolog et al. (2022). While these findings support the hypothesis, some might argue that in some organisational contexts, individual learning needs or departmental objectives may take precedence over team learning. Additionally, the R^2 value, although significant, suggests that other factors such as individual motivation, leadership support and organisational infrastructure also play crucial roles in the adoption of AI tools, as noted by Mazzetti and Schaufeli (2022).

In summary, the support for H4 emphasises the importance of team learning in adopting AI-driven learning tools. However, the approach to fostering a team-learning environment must be context-specific, considering the unique dynamics of each organisation. While collaborative learning can significantly enhance the adoption of AI tools, the process involves navigating various challenges, including aligning team-learning initiatives with organisational goals and individual learning needs.

5.4.5 Hypothesis 5 (H5): Discussion

In relation to Hypothesis 5 (H5), the study explored the impact of shifts in mental models brought about by prior learning and development programmes on engagement with AI-driven personalised learning tools. The hypothesis was significantly supported, suggesting a meaningful relationship between these factors. The affirmation of Hypothesis 5 aligns with the principles highlighted by Senge (2006) that are associated with the concept of mental models, part of his Five Disciplines of a Learning Organisation. This concept is echoed in the works of authors such as Hoe (2019) and Marik (2022), who affirm the transformational impact of reshaping mental models through learning experiences.

The regression analysis yielded a significant positive relationship ($B = .486$, $p < 0.01$), with approximately 18.9% of variance in the intention to adopt AI tools explained by shifts in mental models. The statistical analysis demonstrated a significant positive relationship between shifts in mental models as a result of prior learning experiences and the readiness to use AI tools for ongoing learning ($R^2 = 0.189$). This indicates that changes in mental models significantly influence

the adoption of AI-driven personalised learning tools. These results underscore the importance of mental models, a concept central to Senge's Learning Organisation theory, in the adoption of new technologies. The outcome suggests that employees who have experienced changes in their thinking and perspectives through prior learning are more inclined to engage with AI-driven tools for learning.

The findings corroborate the notion that adaptive mental models foster a readiness to embrace innovative technologies such as AI. This is aligned with the ideas proposed by Hoe (2019), who emphasises the need to challenge existing mental models to adapt to digital disruptions. The shift in mental models can be interpreted as a move towards a more open, innovative mindset, which is crucial for integrating AI into learning processes. This interpretation resonates with Marik's (2022) study, which illustrates the evolution of mental models through reflective practices in leadership development programmes. This shift likely translates to a greater willingness to experiment with and adopt AI-driven personalised learning tools, as learners with evolved mental models are more receptive to new forms of learning and development.

Reflectively, it is important to acknowledge that changing mental models is a complex and often challenging process. Not all learning experiences lead to a transformative change in thinking. Chirico et al. (2022) argue that transformative changes in thinking are not an inevitable outcome of all learning experiences. They further suggest that certain employees may exhibit resistance to such paradigm shifts, a phenomenon that could be attributed to deeply ingrained beliefs about or apprehensions towards unfamiliar concepts. Furthermore, the effective implementation of programmes that are designed to shift mental models requires careful planning, a supportive learning environment, and a sustained commitment from both the organisation and its employees, as highlighted by Le et al. (2022). While the study findings support the hypothesis, it is essential to consider alternative viewpoints. One might argue that the R^2 value, although meaningful, indicates that other factors such as organisational culture, leadership support and technological infrastructure also significantly impact this adoption (Mazzetti & Schaufeli, 2022).

In conclusion, that the results support H5 highlights the critical role of reshaping mental models in the adoption of AI-driven learning tools. However, this process is nuanced and context dependent. Organisations that aim to leverage AI tools effectively must consider the multifaceted nature of learning and development, ensuring that initiatives are comprehensive, inclusive, and aligned with both individual and organisational goals.

5.4.6 Hypothesis 6 (H6): Discussion

Hypothesis 6 (H6) was used to assess the influence of systems thinking on the perception of AI-driven personalised learning tools as beneficial. The hypothesis was substantially supported, indicating a significant correlation between these elements. Hypothesis 6's validation is in harmony with Senge's (2006) concept of systems thinking, a key discipline of a learning organisation. The importance of systems thinking is supported by literature such as Hutasuhut et al. (2021) and Hoe (2019), which highlight the value of the holistic approach to understanding organisational dynamics and decision-making.

The regression model revealed a significant positive relationship ($B = .578$, $p < 0.01$), explaining 31.1% of the variance in the perceived benefits of AI-enhanced learning. This finding indicates that systems thinking, which involves understanding the interconnections within an organisation, significantly enhances the perception of AI's benefits. Employees who view their work environment holistically are more likely to appreciate how AI can contribute to overall organisational learning and development. Systems thinking, which promotes a holistic view of interconnected systems, seems to play a crucial role in how individuals evaluate AI tools for learning. The regression analysis demonstrated a substantial positive relationship between the value placed on systems thinking and the perceived benefits of AI-driven learning tools ($R^2 = 0.311$). This indicates that employees who embrace a holistic and interconnected view of their work environment are more likely to recognise the advantages of AI in learning.

The results align with the principles of systems thinking outlined by Senge (2006), which suggest that understanding the broader context and interconnections enhances the ability to anticipate and adapt to complex scenarios. Individuals with a systems thinking mindset are better equipped to understand the multifaceted benefits of AI-driven tools, appreciating not just the immediate learning outcomes but also their impact on larger organisational goals and processes. This interpretation is consistent with Hutasuhut et al. (2021), who highlight that systems thinking enables employees to make informed decisions in complex scenarios. The finding reflects the idea that systems thinking allows for a more nuanced understanding of AI in learning, recognising its role in the broader context of organisational learning and development.

Reflectively, while systems thinking can significantly influence the adoption and perceived effectiveness of AI-driven learning tools, it is part of a broader set of organisational capabilities and cultures. For AI tools to be effectively integrated and perceived as beneficial, organisations must also ensure that these tools are user-friendly, meet the actual learning needs of employees,

and are supported by a culture that values innovation and continuous learning (Weinstein et al., 2019). While the findings strongly support H6, some might argue that individual technological proficiency or specific organisational needs could independently drive the perceived benefits of AI in learning, irrespective of systems thinking (Leso et al., 2023). Another consideration is the complexity of fostering systems thinking in a diverse workforce. Hoe (2019) suggests that employees bring a diverse range of experiences and cognitive styles to the workplace, and not all may readily embrace or derive benefit from a systems thinking approach.

In summary, the support for H6 highlights the importance of systems thinking in shaping positive perceptions of AI in learning. However, fostering this mindset requires strategic effort and should be complemented by a focus on the broader organisational context, technological capabilities and individual learning needs.

5.4.7 Hypothesis 7 (H7): Discussion

Hypothesis 7 (H7) posits that a supportive regulatory environment positively influences attitudes toward AI-driven personalised learning tools. The results significantly supported this hypothesis, highlighting the pivotal role of regulatory frameworks in shaping technology-adoption attitudes. Hypothesis 7 aligns with the environmental dimension of the TOE framework, which concerns the influence of external factors such as regulatory support on technology adoption. Studies such as that by Pan et al. (2022) have shown that government initiatives and policies play a crucial role in shaping the technology landscape.

The regression analysis for H7 indicated a significant relationship between a supportive regulatory environment and positive attitudes towards AI-driven personalised learning tools ($R^2 = 0.242$). This highlights the critical role of government policies and industry regulations in fostering an environment conducive to AI adoption. Organisations should actively engage with regulatory bodies to ensure that policies are supportive and that they leverage these frameworks to enhance their AI implementation strategies. The analysis indicated a significant positive correlation ($B = .504$, $p < 0.01$) between supportive regulatory environments and perceived benefits of AI-enhanced learning, explaining 24.2% of the variance. This finding suggests that when regulatory environments are perceived as supportive of technological innovation, individuals are more likely to recognise and appreciate the benefits of AI-driven learning tools. The regulatory context appears to provide a framework within which the potential of AI can be explored and understood, affecting the perception of its benefits in the workplace learning context.

The results resonate with the literature on the importance of regulatory frameworks in fostering technology adoption, as mentioned above. As suggested by Depietro et al. (1990), the environmental dimension of the TOE framework emphasises how external factors, including government regulations, impact technology adoption. This interpretation aligns with the views of scholars such as Pan et al. (2022), who discuss the government's role in promoting innovation and technology adoption. The findings indicate that regulatory support does not just facilitate the adoption of AI but also shapes the perception of its effectiveness and utility in personalised learning. It underscores the notion that a regulatory environment that is conducive to AI adoption can alleviate concerns and foster a more favourable view of AI's role in enhancing learning and development (Leso et al., 2023).

While the study supports H7, it is important to recognise that regulatory support is just one aspect of the complex environment that influences AI adoption. Counterarguments suggest that factors such as organisational culture, leadership support and employee readiness for technology may play equally, if not more, significant roles in the adoption of AI-driven learning tools. Moreover, excessive regulatory intervention has the potential to suppress innovation, in this way obstructing the swift evolution and implementation of AI solutions. This view aligns with the conclusions reached by de Almeida et al. (2021), whose research points to the importance of a balanced regulatory framework in the context of AI. This suggests that a balance needs to be struck between regulation and innovation. Over-regulation can impede technological progress, while under-regulation may lead to ethical and privacy concerns.

Reflectively, the support for H7 underscores the importance of a conducive regulatory environment in shaping attitudes towards including AI in learning. However, it is essential to approach this environment within a broader ecosystem that includes internal organisational factors and broader market and technological trends. Policymakers, organisations and AI developers should collaborate to create a regulatory environment that promotes innovation while ensuring ethical and responsible use of AI.

5.4.8 Hypothesis 8 (H8): Discussion

Hypothesis 8 (H8) suggests that competitive pressures in organisations positively impact employees' attitudes toward AI-driven personalised learning tools. The results confirmed this hypothesis, indicating a notable influence of competitive dynamics on the perception and valuation of AI technologies in workplace learning. Hypothesis 8 is rooted in the environmental dimension of the TOE framework, particularly focusing on competitive pressures as a driver of technology adoption. The confirmation of the hypothesis aligns with the findings of studies such as Gangwar et al. (2015) and Chen et al. (2021), which illustrate how competitive dynamics in the market influence the adoption and perception of new technologies.

The analysis demonstrated a significant positive correlation ($B = .446$, $p < 0.01$) between competitive pressures and the perceived effectiveness of AI-driven learning tools, explaining 22.5% of the variance. This finding signifies that as employees perceive greater competitive pressures to adopt technology, their perception of the value of AI-driven learning tools as effective resources increases. This suggests that the drive to maintain or gain a competitive edge in the market can motivate employees to adopt and value innovative technologies such as AI in their learning processes.

These results align with existing literature that highlights the role of competitive pressure in technology adoption, as outlined in the TOE framework by Depietro et al. (1990). The study's findings reflect insights from Gangwar et al. (2015) and Chen et al. (2021), who discuss how competitive dynamics alter the rate of technology adoption and the perceived necessity of such innovations in industries. These insights suggest that in a competitive business landscape, staying updated with technological advancements such as AI becomes not only a strategic advantage but also a perceived necessity for employees. The results also resonate with the notion that competitive pressures can act as a catalyst for embracing and valuing new technologies (Gupta et al., 2022), thus fostering a technology-forward culture within organisations.

While the results support H8, it is important to address counterarguments that emphasise internal organisational factors, such as culture and leadership, as potentially more influential than external competitive pressures. The effectiveness of AI in personalised learning may depend more on how well the technology aligns with the organisation's internal processes, values and learning culture (Seo et al., 2021). Furthermore, overly focusing on competition can lead to rushed or misaligned AI implementations. Organisations may be inclined to integrate AI tools primarily as a reaction to competitive market forces, rather than as a strategic alignment with their learning needs and

objectives. This approach, as suggested by Dung's (2023) analysis of AI misalignment, could potentially impede the effective utilisation of AI in learning and development processes.

Reflectively, the support for H8 highlights the importance of understanding and responding to market dynamics. However, it is crucial for organisations to balance competitive responses with strategic alignment to their unique contexts. Effective AI implementation should be driven by a clear understanding of how it can enhance learning and development, tailored to organisational needs and culture, rather than solely by the desire to keep up with competitors.

5.5 Conclusion

In conclusion, this chapter synthesises the intricate relationship between AI and personalised learning in the workplace, highlighting the crucial roles of individual attitudes, organisational culture and external factors. The discussions, which are grounded in empirical evidence and existing literature, offer valuable insights into the strategic and mindful adoption of AI in enhancing learning experiences, while also acknowledging the complexities and challenges that accompany this technological integration. As organisations continue to navigate the evolving landscape of AI in learning, this study contributes to a deeper understanding and provides a framework for future research and practical application in the field.

Chapter 6: Conclusion and Recommendations

6.1 Introduction

This research provides insights regarding the integration of AI into personalised workplace learning. Key findings are a positive perception of AI's potential for enhancing learning experiences; moderate engagement in self-directed learning; varying perceptions of AI implementation factors; and significant relationships between AI tool adoption and organisational factors such as team learning, systems thinking and personal vision (Georgieff & Hyee, 2022). These findings are important as they illuminate the multifaceted nature of AI adoption in learning environments, highlighting not just technological readiness but also the importance of organisational culture and individual attitudes towards AI (Bader & Kaiser, 2019).

This chapter begins by presenting concluding insights in relation to the research objectives. It then outlines the contribution of the research to the AI field for both academics and those implementing AI in learning practice. This is followed by recommendations for organisational leaders, educators and trainers, and policymakers. The chapter concludes by offering suggestions for further research.

This study was guided by specific research objectives and supported by empirical data. Based on the conceptual framework proposed earlier in Figure 2, the research objectives guided the alignment of the study with the various dimensions of the TOE framework (Depietro et al., 1990) and Senge's Learning Organisation theory (Senge, 2006). However, following the formulation of our hypotheses within these dimensions, the alignment of the hypotheses with the research objectives has slightly shifted. The sections below present the key findings and conclusions according to the research objectives that informed the hypotheses of this research.

6.2 Conclusion pertaining to Research Objective 1: Influence of AI on Personalised Learning and Development in the Workplace

Investigating the influence of AI on personalised learning and development in the workplace (RO1) intersects notably with Hypotheses 1, 3 and 5, each of which addresses distinct facets of AI's impact in this context.

This research demonstrates that AI significantly enhances personalised learning and development in the workplace. The confirmed hypotheses that underpin this objective establish a strong positive correlation between AI's perceived advantages in self-directed learning and its effectiveness over traditional methods (H1), which confirms the transformative potential of AI in customising learning experiences to individual needs (de Laat et al., 2020; Kolog et al., 2022). Additionally, the alignment of AI-driven learning tools with individual professional development goals (H3) is shown to be a key factor in the adoption of AI-driven learning tools (Al-Dhuwaihi et al., 2020; Hutasuhut et al., 2021). Furthermore, the study substantiates that shifts in mental models from prior learning experiences improve engagement with AI tools (H5), signifying the crucial role of learning in shaping attitudes towards innovative technologies such as AI (Hoe, 2019; Marik, 2022). Collectively, these findings underscore the pivotal role of AI in revolutionising workplace learning by catering to individual learning styles and professional aspirations.

6.3 Conclusion pertaining to Research Objective 2: Importance of a Continuous Learning Organisational Work Environment for AI-Driven Learning Adoption

The importance of a continuous learning organisational work environment for AI-driven learning adoption (RO2) aligns closely with Hypotheses 2, 4 and 6, underscoring the role of organisational culture in AI integration.

The findings from Hypotheses 2, 4 and 6 highlight that the compatibility of AI-driven learning tools with existing workplace structures significantly influences employees' intentions to adopt these tools (H2), which points to the need for alignment with organisational contexts (Stenberg & Nilsson, 2020; Tongsuksai et al., 2023). The prioritisation of team learning (H4) is identified as a driver for adopting AI-driven tools, indicating that a collaborative learning culture enhances the integration of innovative learning technologies (Al-Dhuwaihi et al., 2020; Hutasuhut et al., 2021). Moreover, systems thinking is shown to impact the perception of AI's benefits in learning significantly (H6), suggesting that a holistic view of workplace dynamics is crucial for appreciating AI's multifaceted role in learning and development (Hoe, 2019; Hutasuhut et al., 2021). These insights affirm that organisational culture, embracing continuous learning, and systemic thinking are instrumental to the successful adoption of AI in learning.

6.4 Conclusion pertaining to Research Objective 3: Key Influential Factors Affecting Personalised AI-Driven Learning in the Work Environment

Exploring key influential factors that affect personalised AI-driven learning within the work environment (RO3) is reflected in Hypotheses 7 and 8, which focus on external influences.

The study identifies and confirms key influential factors that affect the adoption and effectiveness of AI-driven personalised learning within the work environment. Supportive regulatory environments (H7) are found to play a pivotal role in shaping positive attitudes towards AI-driven learning tools (Pan et al., 2022). This finding highlights the importance of external regulatory frameworks in facilitating the ethical use of AI in learning. Additionally, the study confirms that competitive pressures between and within organisations positively impact employees' attitudes toward AI-driven learning tools (H8), pointing to the influence of market dynamics in motivating the adoption and valuation of AI technologies in learning (Chen et al., 2021; Gangwar et al., 2015). These conclusions indicate that both internal organisational factors and external environmental elements are key determinants in the successful implementation and perception of AI in workplace learning.

6.5 Summary of Conclusions

In conclusion, the research objectives cohesively tie together the impact of AI on personalised learning, the role of organisational culture in AI adoption, and the influence of both internal and external factors on shaping the effectiveness of AI-driven learning. These findings offer an understanding of the multifaceted nature of AI in enhancing personalised learning experiences in the workplace, providing insights for future strategies and implementations in this evolving field. The study concludes that AI holds substantial potential to revolutionise personalised learning in the workplace. However, this potential can only be fully realised if organisations proactively support AI integration through the establishment of continuous learning cultures and robust technological and regulatory frameworks. The research underscores the necessity for strategic investment in AI infrastructure, comprehensive training programs, and adaptive organisational policies to leverage the full benefits of AI-driven personalised learning. By fostering an environment conducive to technological innovation and continuous professional development, organisations can significantly enhance employee engagement, skill acquisition, and overall productivity.

Additional findings of the study include a generally positive perception of AI in workplace learning, with employees recognising its potential to enhance learning experiences, albeit with notable concerns about ethical implications and data privacy (Georgieff & Hyee, 2022; Gwagwa et al., 2020). The research also uncovers moderate engagement in self-directed learning activities, which indicates a shift towards more autonomous learning approaches and highlights the evolving dynamics of workplace learning where digital tools increasingly facilitate growth (Budhiraja, 2023; Smith, 2020). Furthermore, the survey results reveal varying perceptions of AI implementation factors, suggesting that while technological readiness is present, cultural and strategic aspects also play a critical role in AI integration within organisations (Bader & Kaiser, 2019; Kitsios & Kamariotou, 2021; Wilkens, 2020).

6.6 Contribution of the Research

This study makes several contributions to the field of AI in workplace learning, particularly through its empirical exploration of a context that has been relatively under-examined in existing literature.

First, this research makes a contribution to the field of AI in personalised learning within the workplace context. Distinct from previous studies that primarily focused on AI's role in educational institutions or its theoretical aspects, this study provides empirical evidence of how AI is perceived and how it can benefit users in professional development settings (Pillai et al., 2023; Vincent-Lancrin & van der Vlies, 2020). This approach fills a gap in the literature by crucially offering real-world data from working professionals in South Africa on the effectiveness, challenges and opportunities of AI in corporate learning environments. It diverges from traditional research trajectories by delivering insights into AI's practical applications rather than focusing solely on its theoretical potential.

Secondly, in terms of exploring organisational culture and learning dynamics, the study contributes by linking the integration and effectiveness of AI-driven learning tools to these facets. It extends the understanding of AI beyond mere technological implementation to include organisational behaviours, attitudes and cultural readiness (Hutasuhut et al., 2021; Senge, 2006). This perspective provides a more holistic view of AI adoption and utilisation in the workplace, addressing a previously noted gap in research where technology was often considered in isolation from its organisational context. By incorporating these broader aspects, the study provides an increased comprehension of AI's role within the complex tapestry of organisational dynamics.

A third contribution of this study is the examination of both individual and external factors that influence the adoption of AI in learning. Unlike prior research that often focused on either the technological aspects or individual attitudes separately, this study integrates these dimensions, offering some understanding of AI adoption (Gangwar et al., 2015). This approach underscores the intricate interplay between individual perceptions, organisational culture and external pressures, in this way enriching the discourse on the effectiveness and acceptance of AI-driven learning tools.

Lastly, beyond its academic relevance, the research notes some implications for various stakeholders, including business leaders, HR professionals and policymakers. The findings offer ideas for integrating AI into learning strategies, addressing potential barriers and capitalising on AI to enhance learning outcomes (Crompton & Burke, 2023; Farmiloe, 2023; Hashim et al., 2022; Weinstein et al., 2019). These implications are crucial for guiding real-world applications and strategies in corporate settings, where the integration of AI into learning and development is increasingly becoming a focal point of innovation and growth.

6.7 Recommendations

In accordance with the study's findings, some recommendations are presented to enhance the implementation and effectiveness of AI-driven personalised learning in the workplace, targeting different stakeholders.

For organisational leaders and HR professionals, the integration of AI tools into organisational learning strategies should be strategically aligned with both individual and team-learning goals, as suggested by Senge (2006) and Hutasuhut et al. (2021). This strategic alignment fosters a harmonised and effective learning environment that leverages AI to meet diverse educational needs. To achieve successful integration, it is essential to develop a comprehensive AI implementation plan that outlines specific learning outcomes, resource allocation, and timelines. This plan should ensure that AI tools are tailored to support both individual career development plans and collective team objectives.

Additionally, fostering a culture of continuous learning is crucial, as it not only encourages but also supports the adoption of AI-driven tools for professional development (Gangwar et al., 2015). Leaders should promote lifelong learning through regular training sessions, workshops, and learning opportunities. Creating support systems such as learning communities and mentorship programs can further encourage ongoing development. Recognising and rewarding employees

who actively engage in continuous learning and development activities is also vital. Addressing ethical and privacy concerns is also paramount, necessitating the implementation of appropriate policies and practices to safeguard data privacy and ethical standards in AI learning applications (Gangwar et al., 2015; Georgieff & Hyee, 2022). Organisations should develop and enforce comprehensive data privacy policies to safeguard employee information. Establishing clear ethical guidelines for AI use ensures transparency and fairness, while providing training on data privacy and ethical considerations to all employees and stakeholders enhances overall compliance and trust.

For educators and training developers, recommendations include the development of customisable and user-friendly AI learning tools. These tools should be tailored to accommodate diverse individual learning styles and professional development needs and should aim at enhancing their applicability and effectiveness (Pillai & Sivathanu, 2020; Vincent-Lancrin & van der Vlies, 2020; Weinstein et al., 2019). Designing AI tools with the end-user in mind ensures they are intuitive and easy to use, while incorporating features that allow learners to tailor their learning experiences to their preferences and needs enhances engagement and effectiveness. Including robust feedback mechanisms to continuously improve the tools based on user input is also essential.

Moreover, providing comprehensive training and support to employees is vital for boosting digital literacy and facilitating the effective use of AI tools (Budhiraja, 2023; Pillai et al., 2023). Implementing digital literacy programs that cover the basics of AI and its applications in learning can significantly enhance understanding and usage. Offering continuous support through help desks, tutorials, and user guides ensures that users have the resources they need to navigate and utilise AI tools effectively. Conducting workshops and training sessions focused on advanced AI tool functionalities and their application in the workplace further enhances professional development.

From a different perspective, policymakers can be advised to create supportive regulatory frameworks that advocate the ethical use of AI in workplace learning while ensuring equitable access to AI-driven learning resources (Leso et al., 2023; Pan et al., 2022). Developing and enforcing standards that ensure ethical AI use in educational contexts is critical. Policymakers should promote initiatives that make AI learning tools accessible to all segments of the workforce, including underserved and marginalised groups. Collaboration with industry leaders, educational institutions, and technology providers is essential to create policies that support innovation while safeguarding ethical standards.

To ensure that AI-driven learning resources are available to all, policymakers should provide funding and grants to support the development and implementation of AI tools in diverse workplaces. Creating policies that mandate the inclusion of diverse populations in AI learning programs is also important. Conducting public awareness campaigns to educate employers and employees about the benefits and ethical considerations of AI in learning can further facilitate broader adoption and ethical implementation of AI technologies.

Following these recommendations, which are grounded in scholarly research, would be instrumental in ensuring a successful, ethical and effective integration of AI into personalised learning environments within the workplace.

6.8 Suggestions for Further Research

The current study makes various suggestions for future research to enhance the understanding of AI in workplace learning. Research avenues include conducting longitudinal studies to assess the long-term impacts and sustainability of AI-driven personalised learning within organisations (Gangwar et al., 2015). Cross-industry comparative studies could also be undertaken to explore how different industry-specific factors influence AI integration (Vincent-Lancrin & van der Vlies, 2020). Additionally, investigating the impact of emerging AI technologies on learning methodologies and outcomes presents an important research subject for understanding the evolving AI landscape in education (Budhiraja, 2023; Pillai et al., 2023). Research on the psychological aspects of AI adoption could provide deeper insights into the individual attitudes and barriers towards AI in learning environments (Georgieff & Hyee, 2022). Lastly, exploring AI-driven learning in diverse cultural and geographical contexts would offer a more global perspective on AI's use in workplace learning (Leso et al., 2023; Pan et al., 2022).

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Appendix A: Survey Instrument

Study Survey questions

Chat bot messaging survey

AI Command >Say hello to the user in a different South African language! <
I'm Spha and I'll be taking your through this survey.
Please click a button below! 👇
<Start the survey> <End Conversation>
What name can I call you, maybe something like an alias? Don't worry, this won't be included in the survey entry. User type in NAME
Demographics
Q1: Hi, {namesurvey} nice to meet you, what is your age range?
1. 18-24
2. 25-34
3. 35-44
4. 45-54
5. 55+

Q2: What is your gender?
1. Male
2. Female
3. Non-binary
4. Prefer not to say

Q3: Great, I'm assuming you work, please type in the industry you are currently employed in?
User type in answer

Q4: How many years of work experience do you have??
1. Less than 1 year
2. 1-5 years
3. 6-10 years
4. 11-15 years
5. More than 15 years

Q5: How familiar are you with technologies that enhance learning using AI?
1. Not Familiar at All
2. Slightly Familiar
3. Neutral
4. Moderately Familiar
5. Very Familiar

Q6: Do you think AI can improve and create personalised learning experiences?
1. Strongly Disagree
2. Disagree
3. Neutral
4. Agree
5. Strongly Agree

Q7: Are you concerned about the implementation of AI at your workplace for learning purposes?

1. Not Concerned at All
2.Slightly Concerned
3.Neutral
4.Moderately Concerned
5.Very Concerned

Q8: How frequently do you engage in self-directed learning activities within the workplace?
1. Very Rarely
2. Rarely
3. Occasionally
4. Often
5. Very Often

Q9: And how likely are you to adopt AI-driven personalised learning tools in your workplace in the near future?
1. Very unlikely
2. Unlikely
3. Neutral
4. Likely
5. Very likely

Q10: How important is self-directed learning in improving your skills in your current job?
1. Not Important at All
2. Slightly Important
3. Neutral
4. Moderately Important
5. Very Important

Q11: Have you experienced any implementation of AI technologies in your workplace?
1. Never
2. Rarely
3. Sometimes
4. Often
5. Always

Q12: How well does the integration of AI technologies align with your organization's existing systems?
1. Not Well at All
2. Not Well
3. Neutral
4. Well
5. Very Well

Q13: To what extent do you think organisational support influences the success of AI implementation in the workplace?
1. No Influence
2. Very Little Influence
3. Neutral
4. Moderate Influence
5. Strong Influence

H1: *The perceived relative advantage of AI-driven personalised learning over traditional methods will significantly contribute to enhancing skill development and learning experiences for employees in the workplace.*

Q14: How would you rate the effectiveness of AI-driven personalised learning compared to traditional methods in enhancing skill development and learning experiences in the workplace?
1. Strongly Less Effective
2. Less Effective
3. Equally Effective
4. More Effective
5. Much More Effective

H2: *Participants who perceive a strong compatibility between AI-driven personalised learning tools and the existing workplace structure will exhibit a greater intention to adopt these tools for personalised workplace learning and development.*

Q15: To what extent do you believe that AI-driven personalised learning tools fit seamlessly into the existing workplace structure for personalised learning and development?
1. Not Compatible at All
2. Slightly Compatible
3. Somewhat Compatible
4. Very Compatible
5. Extremely Compatible

H3: *Participants who perceive alignment between their personal visions for skill improvement and the opportunities offered by AI-driven personalised learning tools within the organisational environment will exhibit a heightened intention to embrace these tools for continuous learning in the workplace.*

Q16: Do you believe that AI-driven personalised learning tools can align with your personal visions for skill improvement within your organisational environment?
1. Strongly Disagree
2. Disagree
3. Neutral
4. Agree
5. Strongly Agree

H4 *Organizations that prioritise team learning as a mechanism for collaborative skill development within a continuous learning organisational culture will be more inclined to adopt AI-driven personalised learning tools for their employees.*

Q17: To what extent do you believe that prioritising team learning for collaborative skill development within a continuous learning organisational culture positively influences the adoption of AI-driven personalised learning tools?
1. Not Influential at All
2. Slightly Influential
3. Neutral
4. Moderately Influential
5. Highly Influential

H5: *Participants who have undergone shifts in their mental models through prior learning and development programs will demonstrate a heightened readiness to embrace AI tools that facilitate ongoing learning opportunities within a continuous learning organisational environment.*

***Q18:** How do you perceive the impact of prior learning and development programs on your readiness to embrace AI tools for ongoing learning within an organisation?
1. No Impact
2. Low Impact
3. Neutral
4. Moderate Impact
5. High Impact

H6: *Participants who value a holistic perspective shaped by systems thinking will exhibit greater receptivity to AI-driven personalised learning tools within a continuous learning organizational work environment.*

Q19: How likely are you to embrace AI-driven personalised learning tools that align with a holistic perspective and systems thinking principles in the work environment?
1. Very Unlikely
2. Unlikely
3. Neutral
4. Likely
5. Very Likely

H7: *A supportive regulatory environment that fosters technological innovation and adoption will positively influence attitudes toward AI-driven personalised learning tools in the workplace.*

Q20: How much do you believe a supportive regulatory environment can contribute to creating a positive attitude towards the adoption of AI-driven personalised learning tools in the workplace?
1. No Contribution
2. Low Contribution
3. Neutral
4. Moderate Contribution
5. High Contribution

H8: *Competitive pressures that drive organisations to adopt innovative technologies in order to meet industry standards will have a positive impact on employees' attitudes toward AI-driven personalised learning tools in the workplace.*

Q21: To what extent do you believe that the competitive pressures faced by the organisation to adopt innovative technologies and meet industry standards positively influence your attitude towards the adoption of AI-driven personalised learning tools in the workplace?
1. No Influence
2. Low Influence
3. Neutral
4. Moderate Influence
5. High Influence

Thanks for your participation in this survey_____.

If I were a full-fledged AI personal tutor, I would be offering valuable guidance and profound insights into your personal growth journey based on your input. Regrettably, as I am not, our interaction concludes here. Thank you.

Did you enjoy this chatbot survey?
Yes, no, maybe…

End chat

Website/Email message:

Dear Sir / Madam,

Hello! I'm Siphamandla Msimang, a master's student at Wits Business School. I'm conducting research on how artificial intelligence (AI) can enhance individual learning in the workplace. The supervisor for this research is Dr. Manessah Alagbaoso.

We're exploring the utilisation of AI for personalised workplace learning, while also exploring some of its ethical concerns and challenges linked to AI-enabled technologies in self-directed skills learning and development. We'd love for you to take part in our chatbot survey, which takes just 5-10 minutes.

Your participation has no personal costs or direct benefits, and your responses are anonymous.

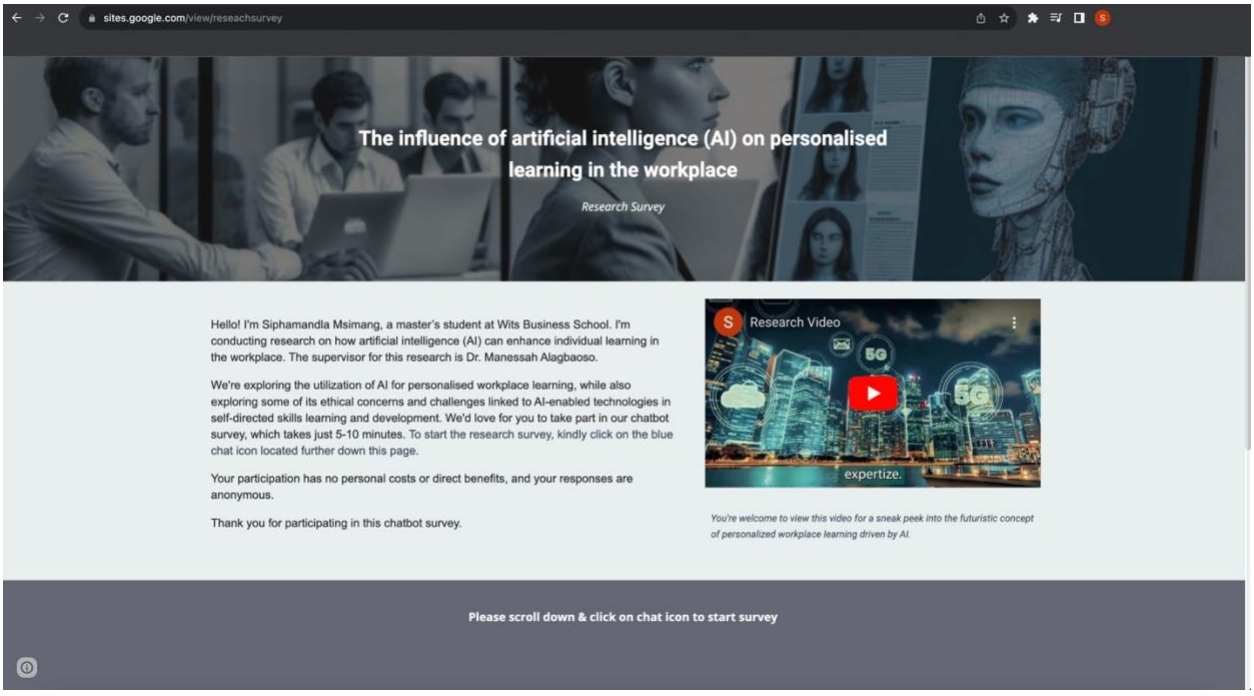
Survey link: https://sites.google.com/view/reseachsurvey

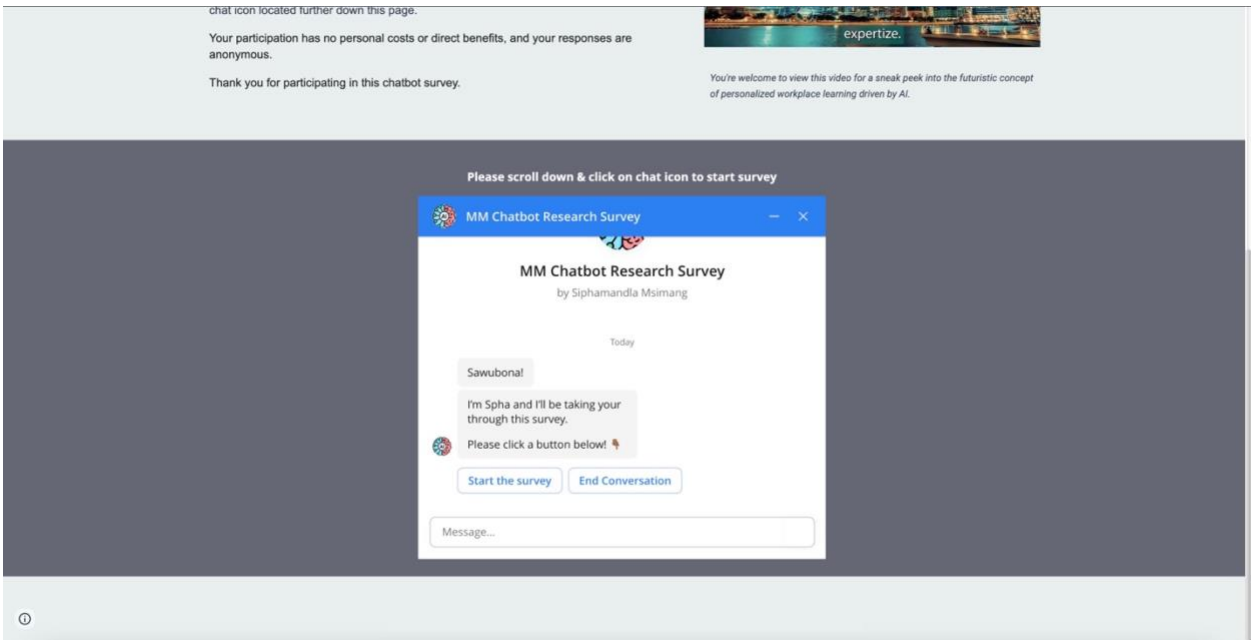
Thank you for participating in this chatbot survey.

Google Site Survey Link

Survey link: https://sites.google.com/view/reseachsurvey

Website containing a brief overview of the research, an original short video and the AI Chatbot Survey.



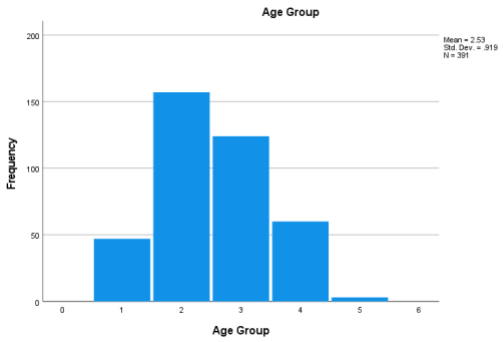


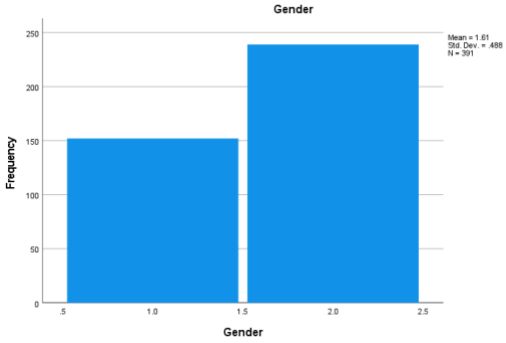
Appendix B: Survey Data

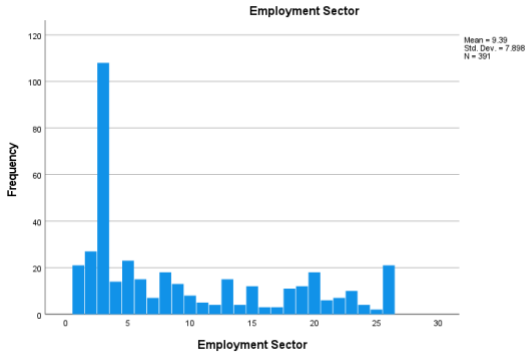
Descriptive Statistics of all the survey questions

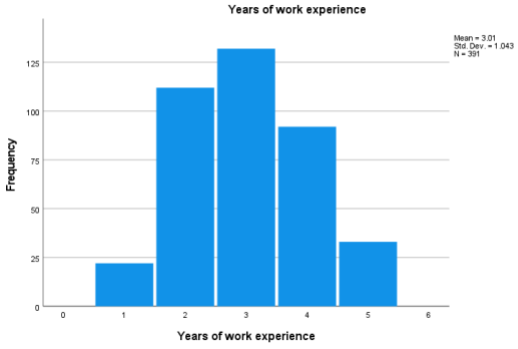
Statistics

		Age Group	Gender	Employment Sector	Years of work experience
N	Valid	391	391	391	391
	Missing	0	0	0	0
Mean		2.53	1.61	9.39	3.01
Median		2.00	2.00	6.00	3.00
Std. Deviation		.919	.488	7.898	1.043



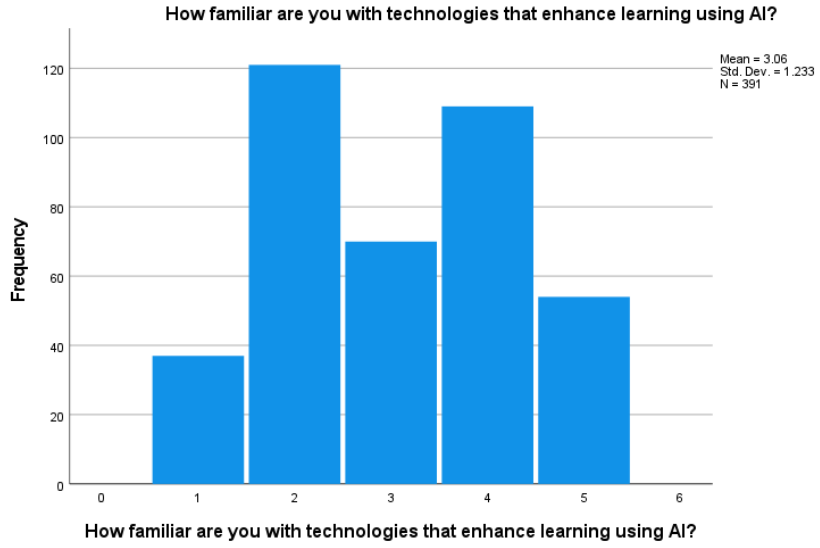






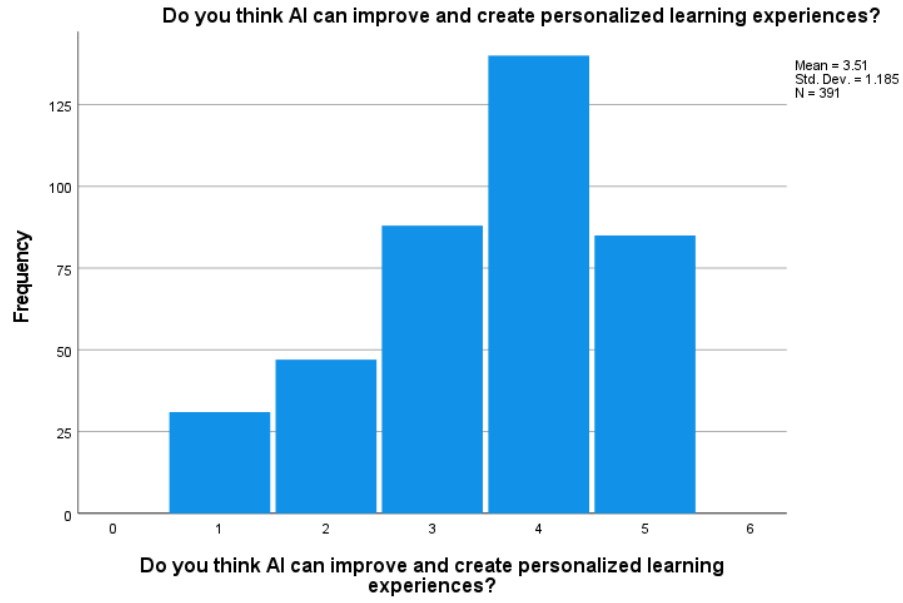
Q5: How familiar are you with technologies that enhance learning using AI?]

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Not Familiar at all	37	9.5	9.5	9.5
	Slightly Familiar	121	30.9	30.9	40.4
	Neutral	70	17.9	17.9	58.3
	Moderately Familiar	109	27.9	27.9	86.2
	Very Familiar	54	13.8	13.8	100.0



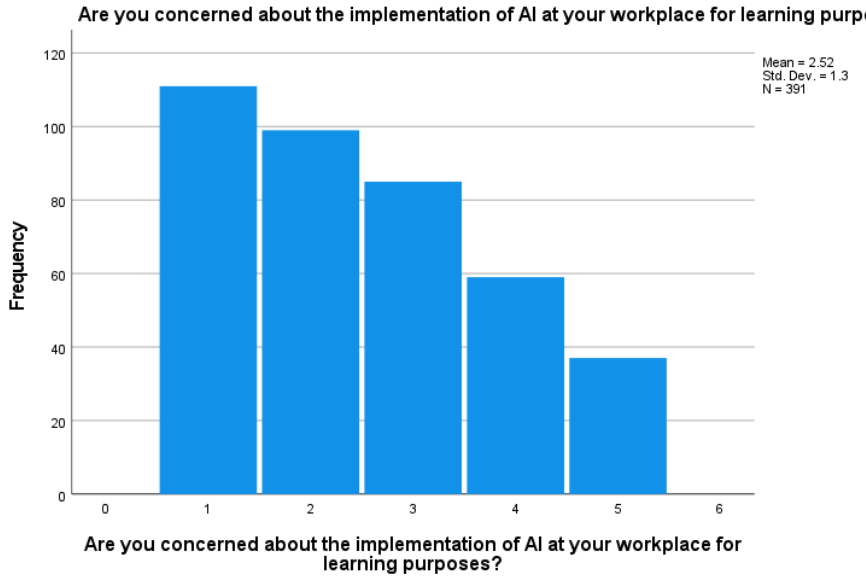
Q6: Do you think AI can improve and create personalized learning experiences?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Disagree	31	7.9	7.9	7.9
	Disagree	47	12.0	12.0	19.9
	Neutral	88	22.5	22.5	42.5
	Agree	140	35.8	35.8	78.3
	Strongly Agree	85	21.7	21.7	100.0



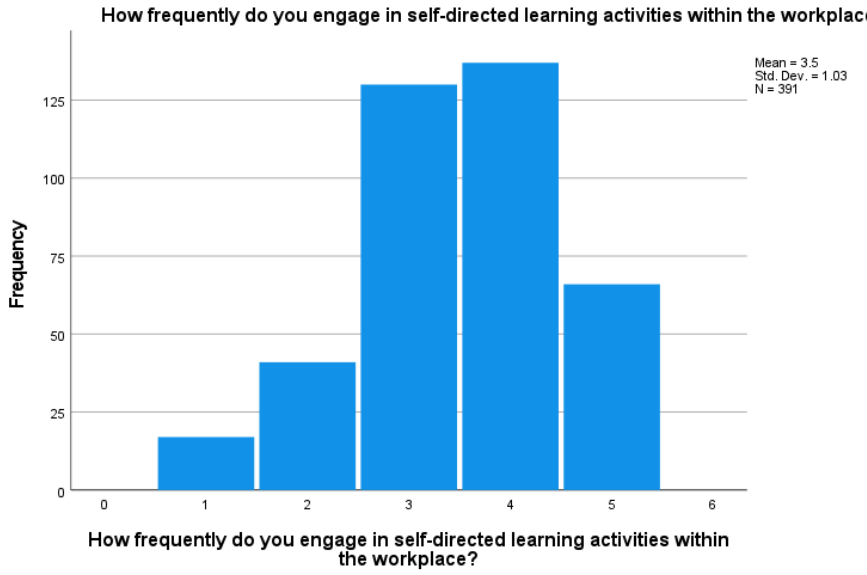
Q7: Are you concerned about the implementation of AI at your workplace for learning purposes?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Not Concerned at All	111	28.4	28.4	28.4
	Slightly Concerned	99	25.3	25.3	53.7
	Neutral	85	21.7	21.7	75.4
	Moderately Concerned	59	15.1	15.1	90.5
	Very Concerned	37	9.5	9.5	100.0



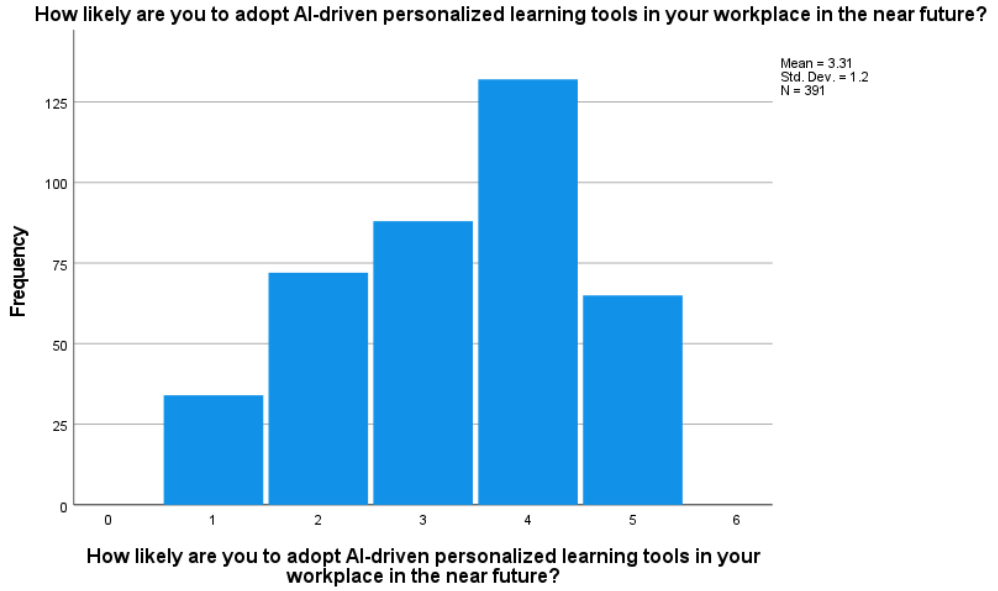
Q8: How frequently do you engage in self-directed learning activities within the workplace?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Very Rarely	17	4.3	4.3	4.3
	Rarely	41	10.5	10.5	14.8
	Occasionally	130	33.2	33.2	48.1
	Often	137	35.0	35.0	83.1
	Very Often	66	16.9	16.9	100.0



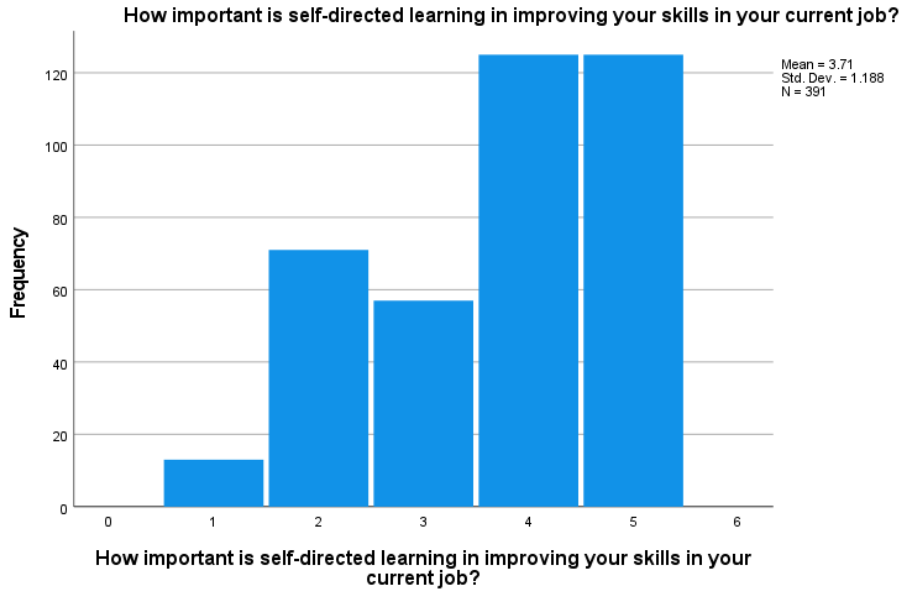
Q9: How likely are you to adopt AI-driven personalized learning tools in your workplace

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Very unlikely	34	8.7	8.7	8.7
	Unlikely	72	18.4	18.4	27.1
	Neutral	88	22.5	22.5	49.6
	Likely	132	33.8	33.8	83.4
	Very Likely	65	16.6	16.6	100.0



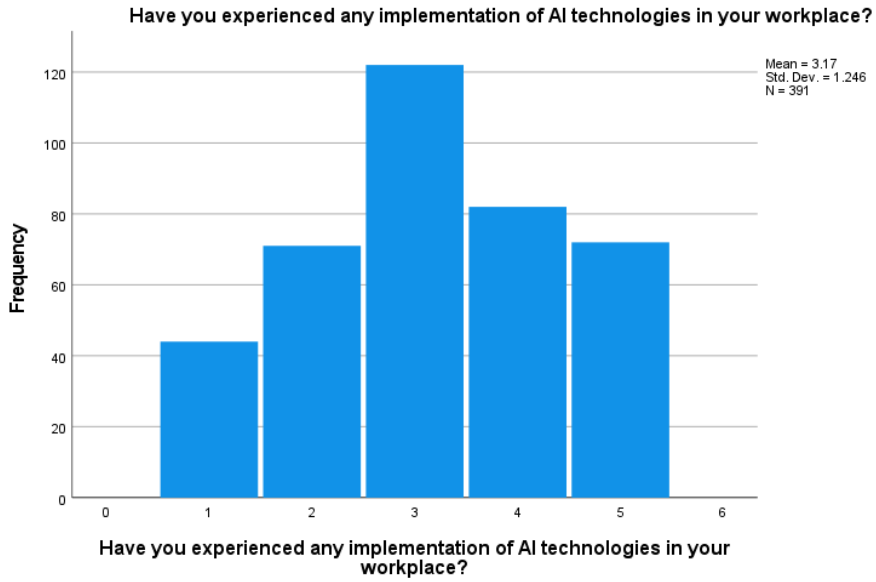
Q10: How important is self-directed learning in improving your skills in your current job?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Not Important at all	13	3.3	3.3	3.3
	Slightly Important	71	18.2	18.2	21.5
	Neutral	57	14.6	14.6	36.1
	Moderately Important	125	32.0	32.0	68.0
	Very Important	125	32.0	32.0	100.0



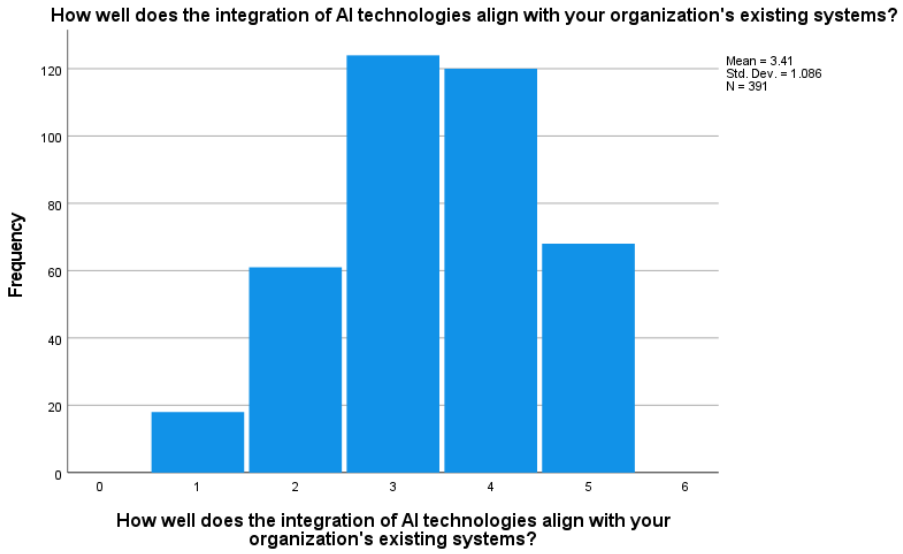
Q11: Have you experienced any implementation of AI technologies in your workplace?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Never	44	11.3	11.3	11.3
	Rarely	71	18.2	18.2	29.4
	Sometimes	122	31.2	31.2	60.6
	Often	82	21.0	21.0	81.6
	Always	72	18.4	18.4	100.0



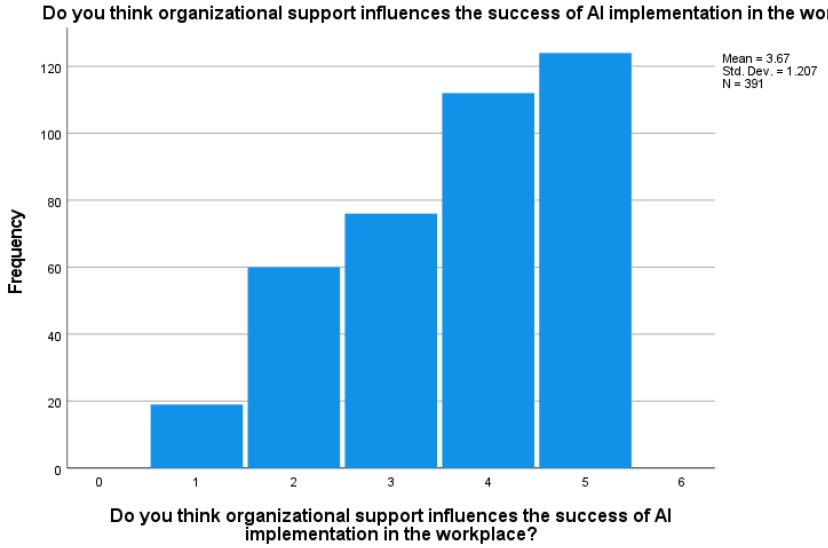
Q12: How well does the integration of AI technologies align with your organization's existing systems?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Not Well at all	18	4.6	4.6	4.6
	Not well	61	15.6	15.6	20.2
	Neutral	124	31.7	31.7	51.9
	Well	120	30.7	30.7	82.6
	Very Well	68	17.4	17.4	100.0



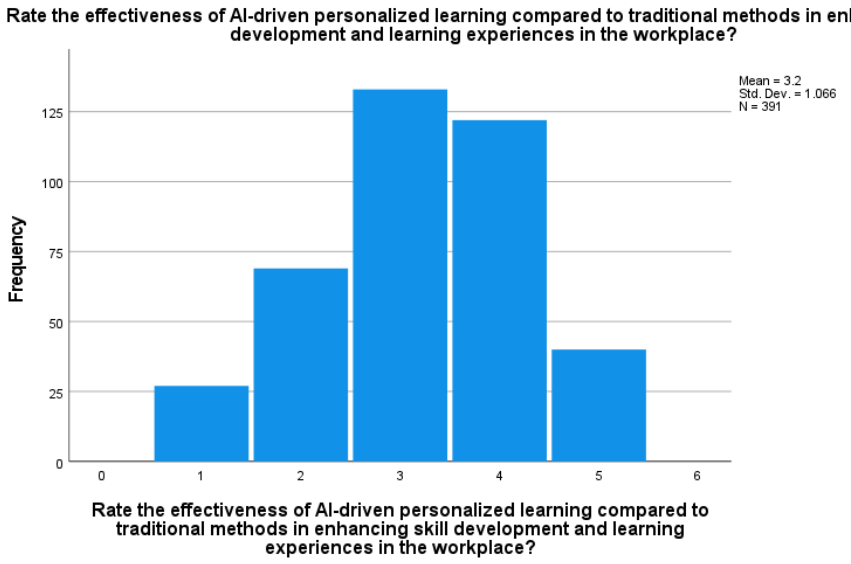
Q13: Do you think organizational support influences the success of AI implementation in the workplace?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No Influence	19	4.9	4.9	4.9
	Very Little Influence	60	15.3	15.3	20.2
	Neutral	76	19.4	19.4	39.6
	Moderately Influence	112	28.6	28.6	68.3
	Strong Influence	124	31.7	31.7	100.0



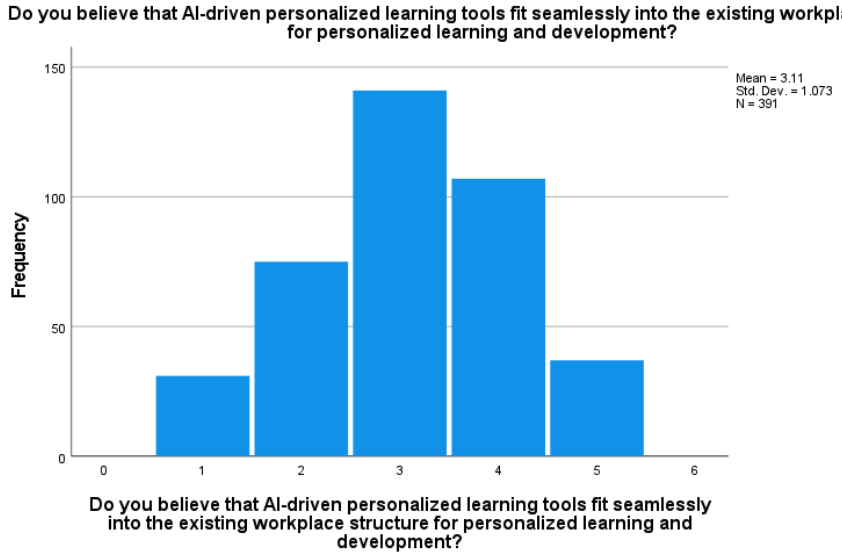
Q14: Rate the effectiveness of AI-driven personalized learning compared to traditional methods in enhancing skill development and learning experiences in the workplace?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Less Effective	27	6.9	6.9	6.9
	Less Effective	69	17.6	17.6	24.6
	Equally Effective	133	34.0	34.0	58.6
	More Effective	122	31.2	31.2	89.8
	Much More Effective	40	10.2	10.2	100.0



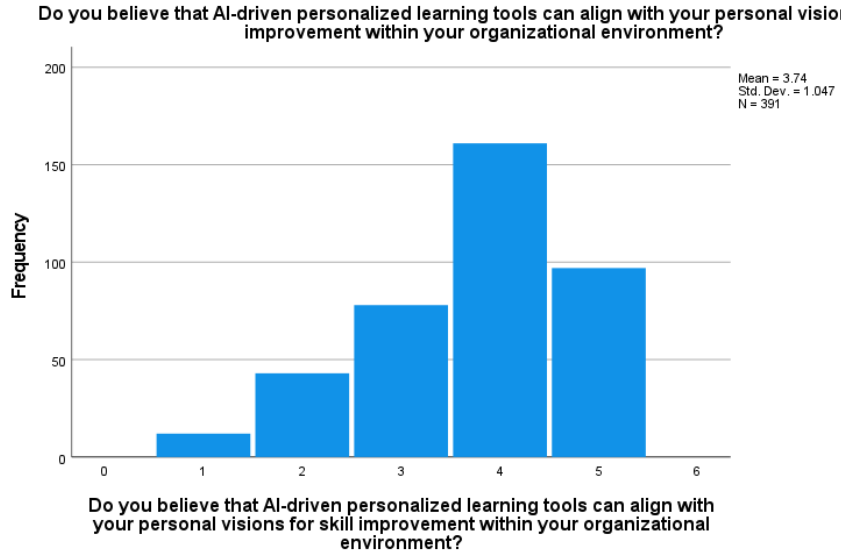
Q15: Do you believe that AI-driven personalized learning tools fit seamlessly into the existing workplace structure for personalized learning and development?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Not Compatible at all	31	7.9	7.9	7.9
	Slightly Compatible	75	19.2	19.2	27.1
	Somewhat Compatible	141	36.1	36.1	63.2
	Very Compatible	107	27.4	27.4	90.5
	Extremely Compatible	37	9.5	9.5	100.0



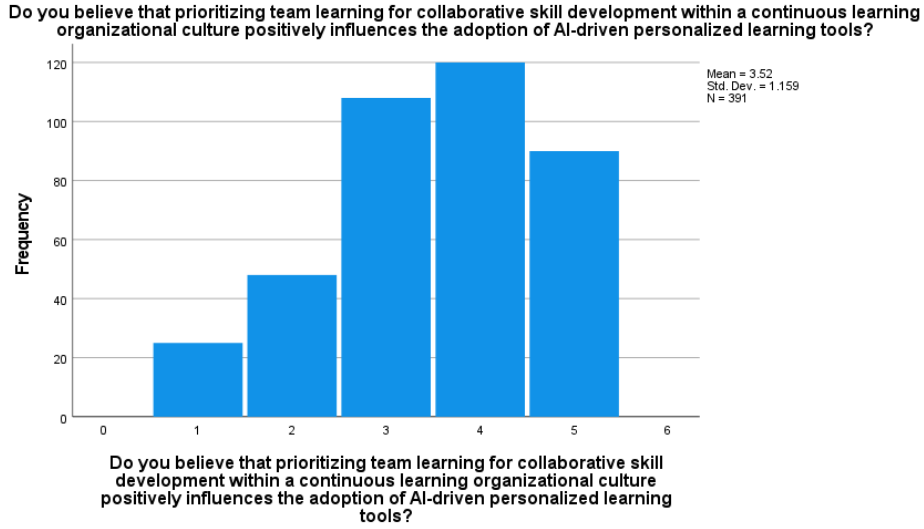
Q16: Do you believe that AI-driven personalized learning tools can align with your personal visions for skill improvement within your organizational environment?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Disagree	12	3.1	3.1	3.1
	Disagree	43	11.0	11.0	14.1
	Neutral	78	19.9	19.9	34.0
	Agree	161	41.2	41.2	75.2
	Strongly Agree	97	24.8	24.8	100.0



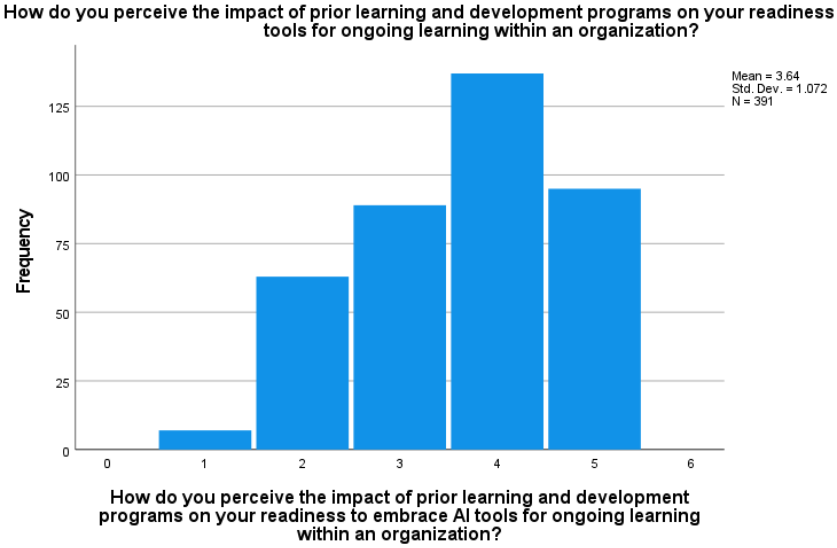
Q17: Do you believe that prioritizing team learning for collaborative skill development within a continuous learning organizational culture positively influences the adoption of AI-driven personalized learning tools?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Not Influential at all	25	6.4	6.4	6.4
	Slightly Influential	48	12.3	12.3	18.7
	Neutral	108	27.6	27.6	46.3
	Moderately Influential	120	30.7	30.7	77.0
	Highly Influential	90	23.0	23.0	100.0



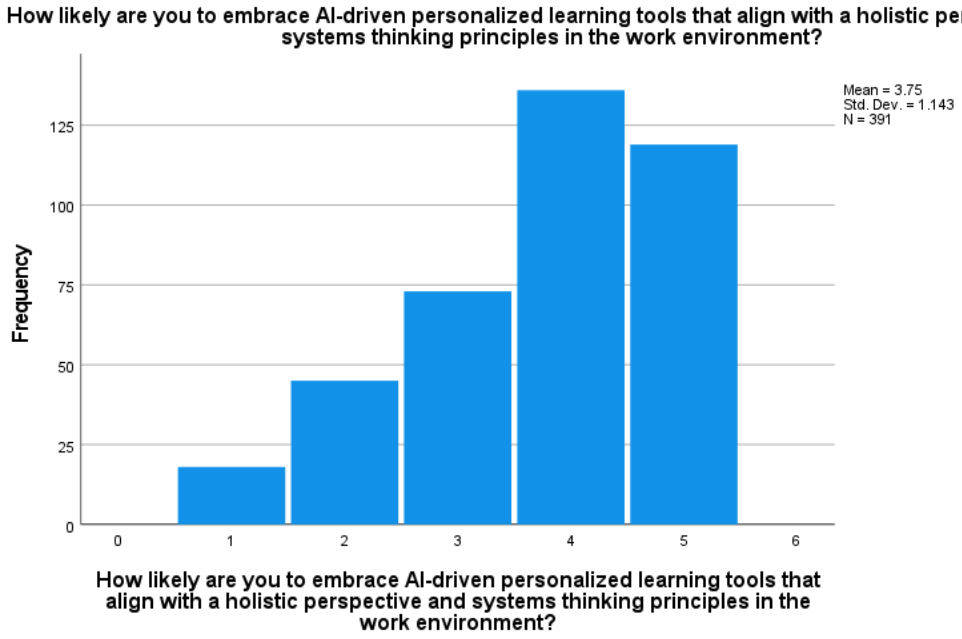
Q18: How do you perceive the impact of prior learning and development programs on your readiness to embrace AI tools for ongoing learning within an organization?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No Impact	7	1.8	1.8	1.8
	Low Impact	63	16.1	16.1	17.9
	Neutral	89	22.8	22.8	40.7
	Moderate Impact	137	35.0	35.0	75.7
	High Impact	95	24.3	24.3	100.0



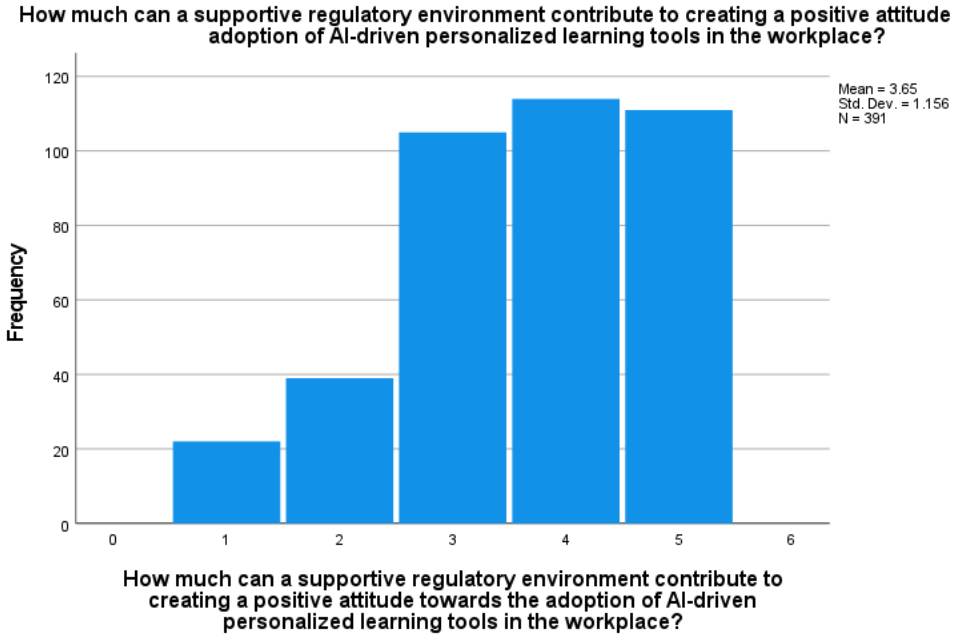
Q19: How likely are you to embrace AI-driven personalized learning tools that align with a holistic perspective and systems thinking principles in the work environment?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Very Unlikely	18	4.6	4.6	4.6
	Unlikely	45	11.5	11.5	16.1
	Neutral	73	18.7	18.7	34.8
	Likely	136	34.8	34.8	69.6
	Very Likely	119	30.4	30.4	100.0



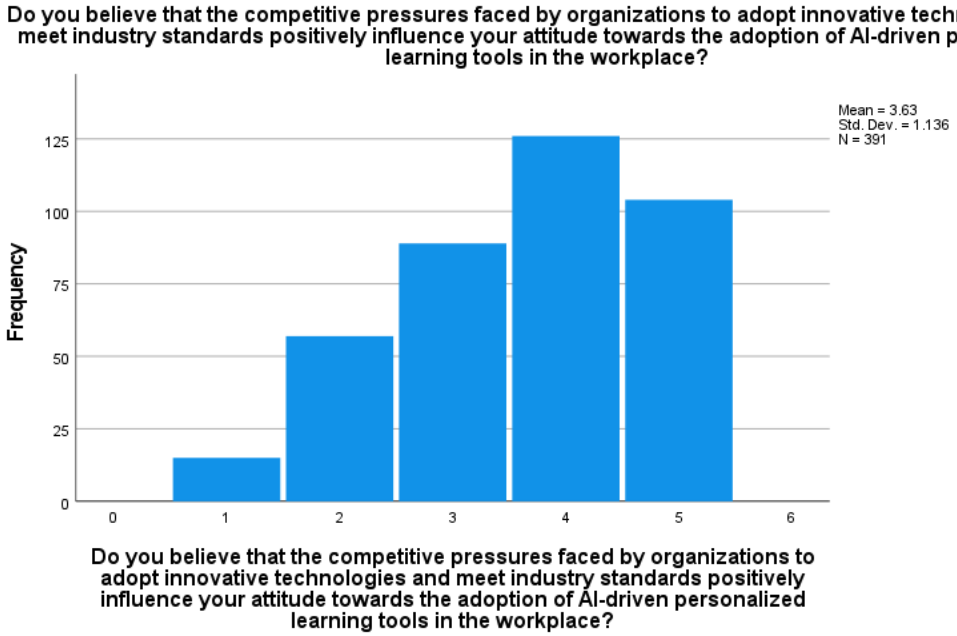
Q20: How much can a supportive regulatory environment contribute to creating a positive attitude towards the adoption of AI-driven personalized learning tools in the workplace?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No Contribution	22	5.6	5.6	5.6
	Low Contribution	39	10.0	10.0	15.6
	Neutral	105	26.9	26.9	42.5
	Moderate Contribution	114	29.2	29.2	71.6
	High Contribution	111	28.4	28.4	100.0



Q21: Do you believe that the competitive pressures faced by organizations to adopt innovative technologies and meet industry standards positively influence your attitude towards the adoption of AI-driven personalized learning tools in the workplace?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No Influence	15	3.8	3.8	3.8
	Low Influence	57	14.6	14.6	18.4
	Neutral	89	22.8	22.8	41.2
	Moderate Influence	126	32.2	32.2	73.4
	High Influence	104	26.6	26.6	100.0



Perception of AI in Workplace Learning

Correlations

		How familiar are you with technologies that enhance learning using AI?	Do you think AI can improve and create personalized learning experiences?	Are you concerned about the implementation of AI at your workplace for learning purposes?
How familiar are you with technologies that enhance learning using AI?	Pearson Correlation	1	.050	-.164**
	Sig. (2-tailed)		.321	.001
	N	391	391	391
Do you think AI can improve and create personalized learning experiences?	Pearson Correlation	.050	1	-.017
	Sig. (2-tailed)	.321		.734
	N	391	391	391
Are you concerned about the implementation of AI at your workplace for learning purposes?	Pearson Correlation	-.164**	-.017	1
	Sig. (2-tailed)	.001	.734	
	N	391	391	391

**. Correlation is significant at the 0.01 level (2-tailed).

Engagement in self-directed learning - Regression Analysis

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.204[a]	.042	.039	1.177

a. Predictors: (Constant), How frequently do you engage in self-directed learning activities within the workplace?

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	23.435	1	23.435	16.929	<,001[b]
	Residual	538.499	389	1.384		
	Total	561.934	390			

a. Dependent Variable: How likely are you to adopt AI-driven personalized learning tools in your workplace in the near future?

b. Predictors: (Constant), How frequently do you engage in self-directed learning activities within the workplace?

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	2.480	.211		11.764	<,001
	How frequently do you engage in self-directed learning activities within the workplace?	.238	.058	.204	4.114	<,001

a. Dependent Variable: How likely are you to adopt AI-driven personalized learning tools in your workplace in the near future?

AI Implementation

Correlations

		Have you experienced any implementation of AI technologies in your workplace?	How well does the integration of AI technologies align with your organization's existing systems?	Do you think organizational support influences the success of AI implementation in the workplace?
Have you experienced any implementation of AI technologies in your workplace?	Pearson Correlation	1	.549**	-.022
	Sig. (2-tailed)		<,001	.665
	N	391	391	391
How well does the integration of AI technologies align with your organization's existing systems?	Pearson Correlation	.549**	1	.097
	Sig. (2-tailed)	<,001		.056
	N	391	391	391
Do you think organizational support influences the success of AI implementation in the workplace?	Pearson Correlation	-.022	.097	1
	Sig. (2-tailed)	.665	.056	
	N	391	391	391

**. Correlation is significant at the 0.01 level (2-tailed).

Inferential Statistics for all hypotheses

Hypothesis 1

Reliability Statistics

Cronbach's Alpha	N of Items
.797	2

Linear Regression

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.667[a]	.444	.443	.795

a. Predictors: (Constant), Do you think AI can improve and create personalized learning experiences?

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	196.904	1	196.904	311.196	<,001[b]
	Residual	246.134	389	.633		
	Total	443.038	390			

a. Dependent Variable: Rate the effectiveness of AI-driven personalized learning compared to traditional methods in enhancing skill development and learning experiences in the workplace?

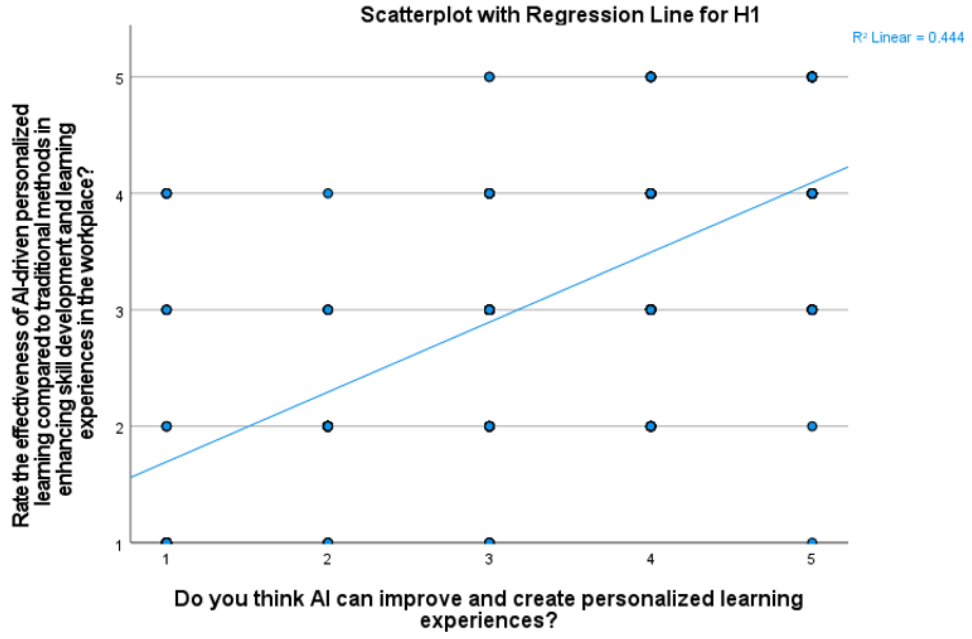
b. Predictors: (Constant), Do you think AI can improve and create personalized learning experiences?

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	1.095	.126		8.688	<,001	.847	1.343
	Do you think AI can improve and create personalized learning experiences?	.600	.034	.667	17.641	<,001	.533	.666

a. Dependent Variable: Rate the effectiveness of AI-driven personalized learning compared to traditional methods in enhancing skill development and learning experiences in the workplace?

Scatterplot



Hypothesis 2

Reliability Statistics

Cronbach's Alpha	N of Items
.765	2

Linear Regression

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.624[a]	.389	.387	.940

a. Predictors: (Constant), Do you believe that AI-driven personalized learning tools fit seamlessly into the existing workplace structure for personalized learning and development?

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	218.548	1	218.548	247.580	<,001[b]
	Residual	343.385	389	.883		
	Total	561.934	390			

a. Dependent Variable: How likely are you to adopt AI-driven personalized learning tools in your workplace in the near future?

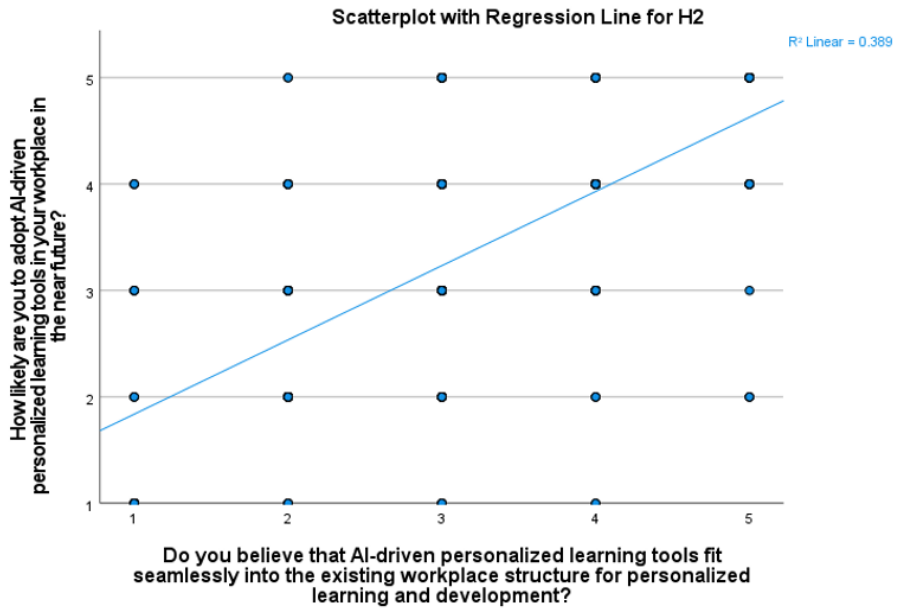
b. Predictors: (Constant), Do you believe that AI-driven personalized learning tools fit seamlessly into the existing workplace structure for personalized learning and development?

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	1.141	.146		7.815	<,001	.854	1.428
	Do you believe that AI-driven personalized learning tools fit seamlessly into the existing workplace structure for personalized learning and development?	.698	.044	.624	15.735	<,001	.610	.785

a. Dependent Variable: How likely are you to adopt AI-driven personalized learning tools in your workplace in the near future?

Scatterplot



Hypothesis 3

Reliability Statistics

Cronbach's Alpha	N of Items
.693	2

Linear Regression

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.286[a]	.082	.079	1.152

a. Predictors: (Constant), Do you believe that AI-driven personalized learning tools can align with your personal visions for skill improvement within your organizational environment?

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	45.899	1	45.899	34.600	<,001[b]
	Residual	516.034	389	1.327		
	Total	561.934	390			

a. Dependent Variable: How likely are you to adopt AI-driven personalized learning tools in your workplace in the near future?

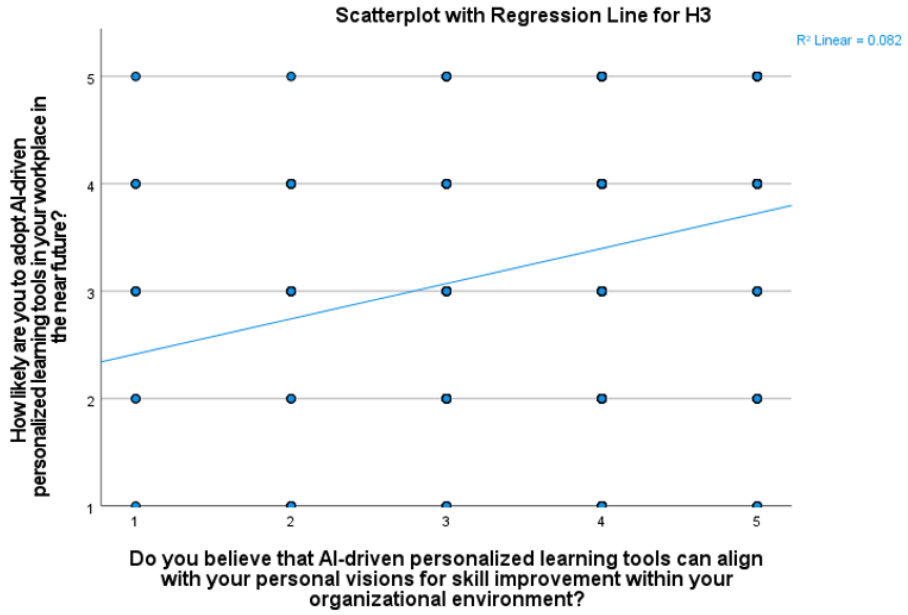
b. Predictors: (Constant), Do you believe that AI-driven personalized learning tools can align with your personal visions for skill improvement within your organizational environment?

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	95,0% Confidence Interval for B Lower Bound	95,0% Confidence Interval for B Upper Bound
1	(Constant)	2.088	.216		9.665	<,001	1.663	2.513
	Do you believe that AI-driven personalized learning tools can align with your personal visions for skill improvement within your organizational environment?	.328	.056	.286	5.882	<,001	.218	.437

a. Dependent Variable: How likely are you to adopt AI-driven personalized learning tools in your workplace in the near future?

Scatterplot



Hypothesis 4

Reliability Statistics

Cronbach's Alpha	N of Items
.533	2

Linear Regression

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.364[a]	.133	.130	1.013

a. Predictors: (Constant), Do you believe that prioritizing team learning for collaborative skill development within a continuous learning organizational culture positively influences the adoption of AI-driven personalized learning tools?

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	61.091	1	61.091	59.522	<,001[b]
	Residual	399.252	389	1.026		
	Total	460.343	390			

a. Dependent Variable: How well does the integration of AI technologies align with your organization's existing systems?

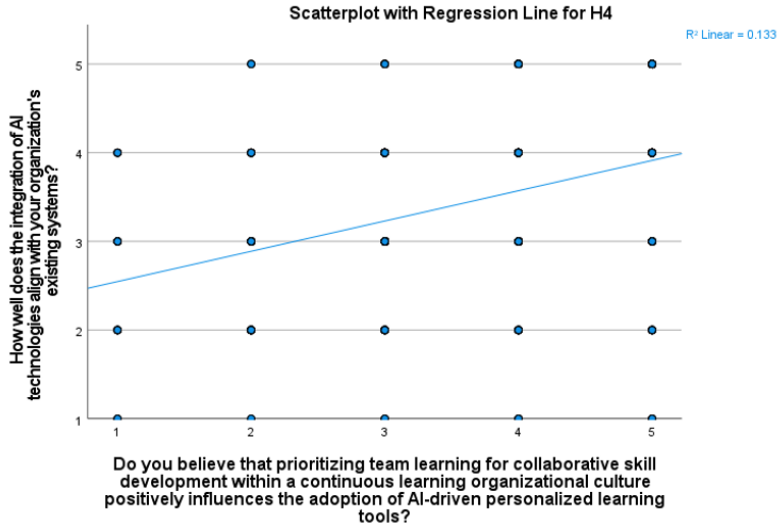
b. Predictors: (Constant), Do you believe that prioritizing team learning for collaborative skill development within a continuous learning organizational culture positively influences the adoption of AI-driven personalized learning tools?

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	2.206	.164		13.456	<,001	1.883	2.528
	Do you believe that prioritizing team learning for collaborative skill development within a continuous learning organizational culture positively influences the adoption of AI-driven personalized learning tools?	.342	.044	.364	7.715	<,001	.255	.429

a. Dependent Variable: How well does the integration of AI technologies align with your organization's existing systems?

Scatterplot



Hypothesis 5

Reliability Statistics

Cronbach's Alpha	N of Items
.603	2

Linear Regression

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.434[a]	.189	.187	1.083

a. Predictors: (Constant), How do you perceive the impact of prior learning and development programs on your readiness to embrace AI tools for ongoing learning within an organization?

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	106.039	1	106.039	90.480	<,001[b]
	Residual	455.894	389	1.172		
	Total	561.934	390			

a. Dependent Variable: How likely are you to adopt AI-driven personalized learning tools in your workplace in the near future?

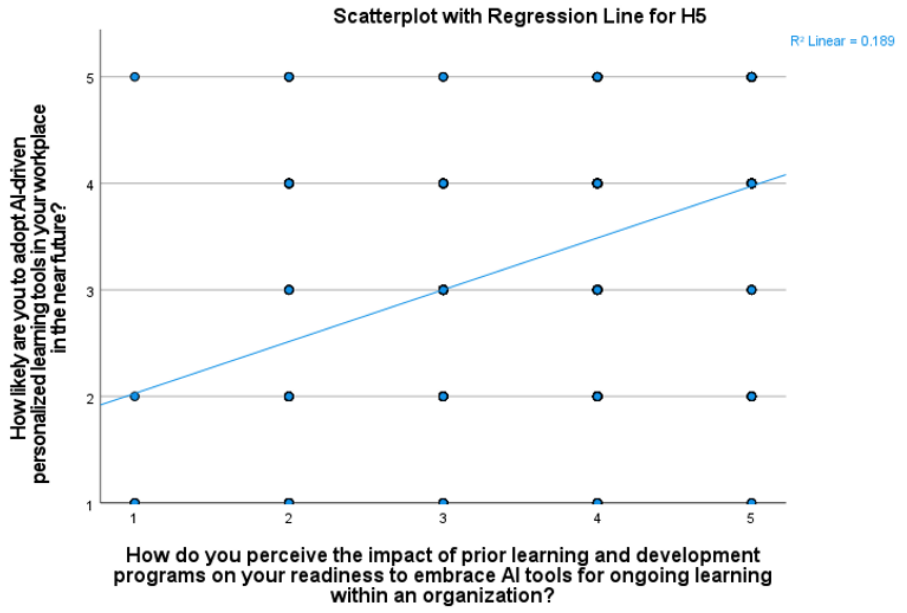
b. Predictors: (Constant), How do you perceive the impact of prior learning and development programs on your readiness to embrace AI tools for ongoing learning within an organization?

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	1.542	.194		7.947	<,001	1.160	1.923
	How do you perceive the impact of prior learning and development programs on your readiness to embrace AI tools for ongoing learning within an organization?	.486	.051	.434	9.512	<,001	.386	.587

a. Dependent Variable: How likely are you to adopt AI-driven personalized learning tools in your workplace in the near future?

Scatterplot



Hypothesis 6

Reliability Statistics

Cronbach's Alpha	N of Items
.715	2

Linear Regression

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.557[a]	.311	.309	.985

a. Predictors: (Constant), How likely are you to embrace AI-driven personalized learning tools that align with a holistic perspective and systems thinking principles in the work environment?

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	170.107	1	170.107	175.258	<,001[b]
	Residual	377.566	389	.971		
	Total	547.673	390			

a. Dependent Variable: Do you think AI can improve and create personalized learning experiences?

b. Predictors: (Constant), How likely are you to embrace AI-driven personalized learning tools that align with a holistic perspective and systems thinking principles in the work environment?

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	1.347	.171		7.877	<,001	1.011	1.684
	How likely are you to embrace AI-driven personalized learning tools that align with a holistic perspective and systems thinking principles in the work environment?	.578	.044	.557	13.239	<,001	.492	.664

a. Dependent Variable: Do you think AI can improve and create personalized learning experiences?

Scatterplot



Hypothesis 7

Reliability Statistics

Cronbach's Alpha	N of Items
.659	2

Linear Regression

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.492[a]	.242	.240	1.033

a. Predictors: (Constant), How much can a supportive regulatory environment contribute to creating a positive attitude towards the adoption of AI-driven personalized learning tools in the workplace?

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	132.628	1	132.628	124.305	<,001[b]
	Residual	415.045	389	1.067		
	Total	547.673	390			

a. Dependent Variable: Do you think AI can improve and create personalized learning experiences?

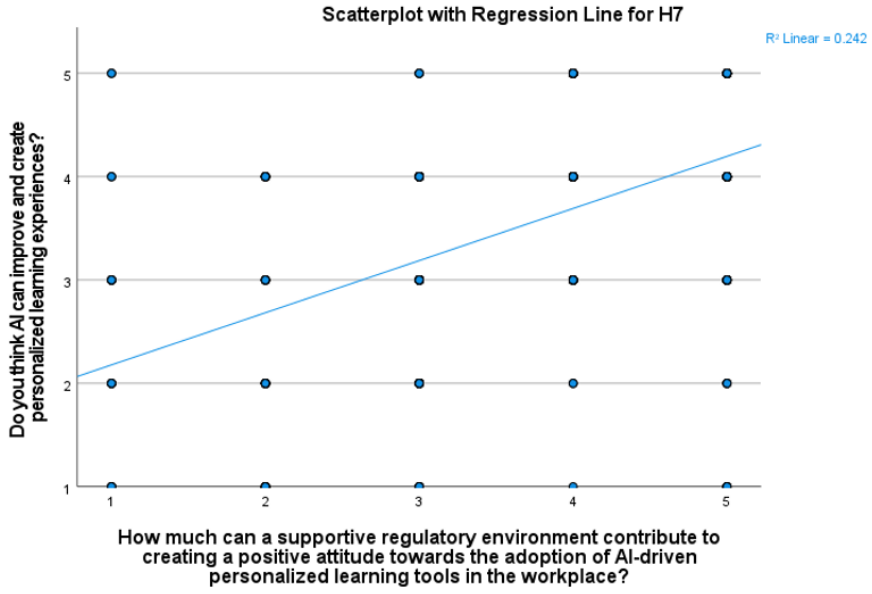
b. Predictors: (Constant), How much can a supportive regulatory environment contribute to creating a positive attitude towards the adoption of AI-driven personalized learning tools in the workplace?

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	95,0% Confidence Interval for B Lower Bound	95,0% Confidence Interval for B Upper Bound
1	(Constant)	1.674	.173		9.675	<,001	1.334	2.015
	How much can a supportive regulatory environment contribute to creating a positive attitude towards the adoption of AI-driven personalized learning tools in the workplace?	.504	.045	.492	11.149	<,001	.415	.593

a. Dependent Variable: Do you think AI can improve and create personalized learning experiences?

Scatterplot



Hypothesis 8

Reliability Statistics

Cronbach's Alpha	N of Items
.643	2

Linear Regression

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.475[a]	.225	.223	.939

a. Predictors: (Constant), Do you believe that the competitive pressures faced by organizations to adopt innovative technologies and meet industry standards positively influence your attitude towards the adoption of AI-driven personalized learning tools in the workplace?

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	99.844	1	99.844	113.171	<,001[b]
	Residual	343.194	389	.882		
	Total	443.038	390			

a. Dependent Variable: Rate the effectiveness of AI-driven personalized learning compared to traditional methods in enhancing skill development and learning experiences in the workplace?

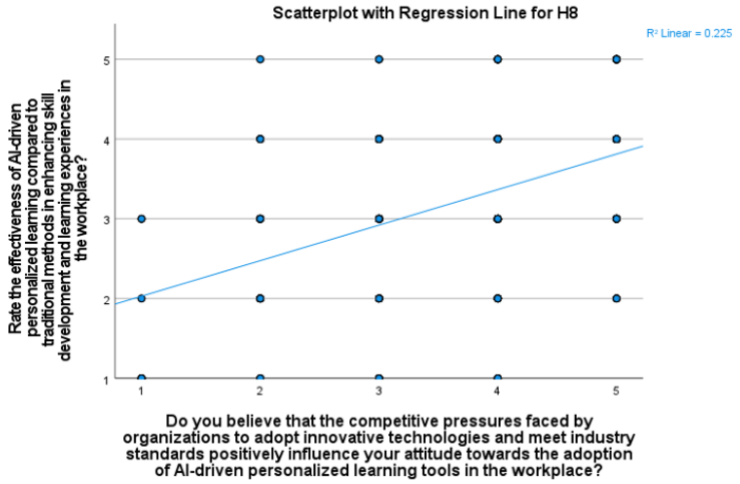
b. Predictors: (Constant), Do you believe that the competitive pressures faced by organizations to adopt innovative technologies and meet industry standards positively influence your attitude towards the adoption of AI-driven personalized learning tools in the workplace?

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients			95,0% Confidence Interval for B	
		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound
1	(Constant)	1.584	.159		9.940	<,001	1.271	1.897
	Do you believe that the competitive pressures faced by organizations to adopt innovative technologies and meet industry standards positively influence your attitude towards the adoption of AI-driven personalized learning tools in the workplace?	.446	.042	.475	10.638	<,001	.363	.528

a. Dependent Variable: Rate the effectiveness of AI-driven personalized learning compared to traditional methods in enhancing skill development and learning experiences in the workplace?

Scatterplot



Appendix C: Ethics approval

UNIVERSITY OF THE WITWATERSRAND, JOHANNESBURG

OFFICE OF THE DEPUTY REGISTRAR

24 October 2023

Siphamandla Msimang
Student Number (2604291)
Master of Management
Wits Business School

TO WHOM IT MAY CONCERN

"The influence of AI on personalised learning in the workplace."

This letter serves to confirm that the above project has received permission to be conducted on University premises, and/or involving staff and/or students of the University as research participants. In undertaking this research, you agree to abide by all University regulations for conducting research on campus and to respect participants' rights to withdraw from participation at any time.

If you are conducting research on certain student cohorts, year groups or courses within specific Schools and within the teaching term, permission must be sought from Heads of School or individual academics.

Ethical clearance has been obtained. (Protocol number: WBS/DB2604291/602)

Research Expiration: (Research submission date)

Potgieter

Nicoleen Potgieter
University Deputy Registrar

Appendix D: Permission Letters

Permission from HR

Tuesday, February 6, 2024 at 16:14:58 South Africa Standard Time

Subject: FW: Permission to conduct research at the HR Department
Date: Monday, 23 October 2023 at 11:39:35 South Africa Standard Time
From: Kgomotso Kasonkola
To: Nicoleen Potgieter
CC: Thato Chauke, Spha Msimang
Attachments: image001.png, image002.png, image003.png, image004.png, image005.png, image006.png, image007.png, Letter requesting Permission HR.docx

Hi Nicoleen,

I do not have an objection in Spha conducting the study on HR colleagues, but I would need your assistance towards final approval. I know that you will need an ethical clearance letter for these purposes.

Best wishes
Kgomotso

From: Spha Msimang <spha.msimang@wits.ac.za>
Sent: Monday, October 23, 2023 10:49 AM
To: Kgomotso Kasonkola <kgomotso.kasonkola1@wits.ac.za>
Subject: Permission to conduct research at the HR Department

Hi Dr Kgomotso Kasonkola

I'm a student and a staff member here at Wits and I'm kindly seeking permission to conduct my research from the Human Resources staff members.

It's a quick and interactive messaging chatbot survey designed to be as painless as possible, it will only take about 5mins for the team to complete. Here is the survey link: https://sites.google.com/view/reseachsurvey

Attached is the official letter requesting permission, you can just simply sign it and send back to me.

Thank you so much and let me know if you need further clarity.

Regards,

Spha Msimang
e-learning Multimedia Designer | **eFundanathi**
e: spha.msimang@wits.ac.za
t: 011 717 3259
a: eZone, Khanya Block-East, WEC
p: 7 York Road, Parktown, 2193
w: https://www.wits.ac.za/therapeuticsciences
s:



Permission from CLTD and HR

UNIVERSITY OF THE WITWATERSRAND, JOHANNESBURG

Dear Sir/Madam,

Re: Permission to conduct research at the Centre for Learning and Teaching Development

Research Title: The influence of artificial intelligence (AI) on personalised learning in the workplace

My name is Siphamandla Msimang, I am a student at the Wits Business School and a staff member in the School of Therapeutic Sciences at the University of the Witwatersrand. I am seeking permission to do research at the Centre for Learning and Teaching Development.

I'm conducting research on how artificial intelligence (AI) can enhance individual learning in the workplace, while also exploring some of its ethical concerns and challenges linked to AI-enabled technologies in self-directed skills learning and development. I believe the staff will add valuable contribution to this study.

I will invite individuals from the organization to participate in this study through an interactive messaging chatbot survey, which takes just 5-10 minutes. Here is the link to the survey: https://sites.google.com/view/reseachsurvey

The participation has no personal costs or direct benefits, and the responses will be anonymous, no personal names will be on the research document.

Kindly grand permission in writing to conduct my research at the department by signing this document.

Yours sincerely,

Spha Msimang
0799528146
spha.msimang@wits.ac.za

Supervisor
Dr. Manessah Alagbaoso
Obinali.Alagbaoso@wits.ac.za

Name: Dr Gerrit Wissing

Department: Director: Centre for Learning and Teaching Development

Signature:

Date: 23 October 2023