Enhancing AI Auto Efficacy: Role of AI Knowledge, Information Source, Behavioral Intention and Information & Communications Technology Learning

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Abstract

This study examines how employees' AI knowledge and understanding affects their auto-efficacy, behavioural intents, and ICT learning in Saudi Arabian software houses. The study seeks to understand how AI knowledge affects these outcomes and discover moderating and mediating factors. A method of quantitative analysis was used with 289 software firm employees. Data were acquired using a structured questionnaire using research-based scales. Data analysis using Partial Least Squares Structural Equation Modelling (PLS-SEM) examined complex construct interactions. AI knowledge significantly affects auto-efficacy, behavioural intention, and ICT learning. Behavioural intention mediates AI knowledge, auto-efficacy, and ICT learning. The impact of AI knowledge on self-efficacy is moderated by information source quality. These findings emphasise AI knowledge and context of AI learning. This study integrates AI-specific features into technology adoption models to improve theory. It highlights how targeted AI training programs and high-quality information sources may raise employee engagement with AI technology, serving as practical advice for companies aiming to improve their technology and workforce readiness.

Keywords

AI Knowledge, Behavioral Intention, Source of Information, AI Auto-Efficacy, Information and Communication Technology Learning.

1. Introduction

Artificial Intelligence also known as AI has impacted many industries because it alters the way organizations work, create, and scheme in the current world. AI at the workplace is shifting company dynamics by altering processes and employee expectations of advanced technology and practices (**Lérias *et al.***, 2024). In order to remain relevant and provide value to organizations, the personnel needs to understand what AI is and how it works (**Candini *et al.***, 2023). The knowledge of AI and its applications enables the employees to harness the AI applications in enhancing the working operation, decision-making processes, and productivity (**Marin; Nilă**, 2021). This shift towards AI adoption for processes entails the organisations to develop AI literacy and self-efficiency to support the adoption and utilisation of compliant technology (**Steels**, 2022). AI has also affected ICT learning in the sense that it leads to increased engagement with the technologies. Knowledge and skills of learning technologies in ICT that are desirable for organisational changes and competiveness (**Al-Hamad *et al.***, 2021). As AI becomes more integrated with ICT platforms, personnel must understand and apply AI principles to improve their IT skills. Research shows that knowing AI helps employees handle a variety of digital technologies and platforms (**Ayanwale *et al.***, 2022). In the context of this study, the impact of AI on learners, employees' performance, acquisition, learning, and behaviour in relation to technology is dynamic hence making it an area of study worthy of consideration. Despite expanding research on AI and ICT learning, additional research is needed on how AI knowledge affects technology-related behaviours, specifically AI auto-efficacy and ICT learning outcomes. This research domain connects with technology adoption, self-efficacy theory, and knowledge transfer, where knowledge and motivation affect technology learning.

Many empirical researches have studied the relationship between technology knowledge, self-efficacy, and learning outcomes, notably in ICT and AI adoption. **Ayanwale *et al.*** (2022) examined how technological knowledge affects people's propensity to accept and learn new tools. This fundamental study demonstrated that prior knowledge of a technology increased self-efficacy and positive behavioural intentions towards its adoption (**Andrews *et al.***, 2021). Knowledge increases self-efficacy in AI, as studies have discovered that understanding AI ideas increases confidence in utilising AI tools (**Hooda *et al.***, 2022). Knowledge acquisition promotes self-efficacy and eases workplace AI adoption. Some findings that have been established in several researches are the impacts of AI knowledge on ICT learning. **Song *et al.*** (2022) also observed that wider ICT learning activities increased with better acquaintance with AI technology; hence, the understanding of the concept of AI quickens digital learning. This corroborates with **Meijer *et al.*** (2018), researcher has also observed that with AI-related training enhances ICT learning outcomes (**Chatterjee *et al.***, 2023). These professionals showed how extending AI knowledge during learning and the application of the AI knowledge to the different technologies (**Jiang *et al.***, 2022). A study by **Akour *et al.*** (2021) revealed that enhancing students' AI knowledge as well as structured learning environments enhance learning as learners spend more time dealing with AI and Non-AI ICT technologies. These results underscore the need to acquire AI knowledge in order to enhance AI-related and general technological literacy. Also, the theoretical research has looked into how information sources influence technological learning (**Wang *et al.***, 2021). In a similar study by **Almaiah *et al.*** (2022) the effectiveness of employee knowledge of AI and its application were highly correlated with legitimacy and relevancy of information sources used in the workplace. This study questions has identified that official training programs and industry specialist are likely to support the employees to better understand AI and enhance their ICT skills (**Kelly *et al.***, 2023). On the other hand, formal knowledge may be deemed insufficient, partial or even wrong sometimes originating from informal or non-specialized sources and therefore limit learning (**Al-Maroof *et al.***, 2022). AI technologies encourage employees to learn the necessary abilities, improving their ICT knowledge. According to **Jang *et al.*** (2021), understanding AI concepts reduces anxiety and boosts technology trust, improving learning. Since AI mediates learning results and learning goals, these findings clearly suggest that knowing AI is essential for learning ICT skills.

Many empirical study has been done on AI knowledge, self-efficacy, and ICT learning (**Flavián *et al.***, 2022); some sectors need more research and expansion. Previous study ignored information sources' moderating effect on AI knowledge and learning results (**Wang *et al.***, 2023a). Little is known about how peer learning, official training programs, and digital platforms affect AI comprehension and ICT learning (**Liao; Sundar**, 2022). Information trustworthiness affects technology adoption. As more firms use these channels to share their AI skills through organised training programs and informal knowledge-sharing platforms, understanding their operation is critical (**Seo *et al.***, 2021). Little empirical study has compared sources and AI learning results. Research on how artificial intelligence knowledge affects behavioural intention and ICT learning is also lacking (**Lee *et al.***, 2021). Existing research has not examined how artificial intelligence knowledge helps behavioural intention become ICT learning. Knowledge affects self-efficacy and technology adoption in many studies (**Aggarwal *et al.***, 2023). Therefore, it is crucial to close this difference since knowledge acquisition mediates employee intentions into actionable learning. It was evident that when the employees' behavioural goals were strong, they were able to learn; however, the authors found a lack of evidence of how such knowledge impacted the learning on ICTs (**Ozturk *et al.***, 2023). Knowledge of artificial intelligence impact on these traits might open a gigantic knowledge gap. AI knowledge may enhance the learners cognitive understanding of ICT ideas than the practical aspects depending on the learning context and application (**Al-Rahmi *et al.***, 2021). These gaps have been outlines would help advance knowledge on AI and ICT learning and informed businesses' AI training.

This research is based on the premise of the Technology Acceptance Model, self-efficacy theory and knowledge transfer theory. According to **Al-Maroof *et al.*** (2022), the Technology Adoption Model (TAM) posits that the adoption of technology is influenced by two key factors: of perceived ease of use and usefulness is obtained. Purposes of this model are to explain effects of AI concepts on behavioural intentions relevant to AI. If employees understand this concept of artificial intelligence in a deeper level, then they are more likely to look at this technology as advantageous and easy to work with. On this basis, this impression contributes to their readiness to use AI technologies in the workplace. From this theory, functional comprehension of the concept of artificial intelligence assists in mediating the relationship between intention and the related actions regarding the technology; which includes; attaining knowledge of ICT information and performing self-relance (**Wang *et al.***, 2023a).

2. Literature Review

Digital, interactive, and personalised learning environments have been created using Information and Communication Technology (ICT) (**Kim; Lee**, 2024). Due to online platforms, digital simulations, and multimedia materials, information is more accessible. This allows pupils to creatively connect with knowledge (**Sayaf *et al.***, 2021). Information and communication technology (ICT) encourages diverse learning styles and speeds, which promotes motivation, involvement, and collaboration (**Mohr; Kühl**, 2021). Web-based learning tools and online exams allow students to change and improve their learning quickly by delivering immediate feedback. Information and communication technology (ICT) for educators allows technology-mediated learning experiences that foster critical thinking, creativity, and problem-solving (**Singh *et al.***, 2021). ICT has enhanced communication between students, teachers, parents, and administrators outside the classroom. Learning Management Systems (LMSs), social media, and messaging platforms promote school collaboration by facilitating continuous communication (**Almarzouqi *et al.***, 2022). ICT has also democratised education by enabling global distant learning and remote education beyond geographical and social borders (**Liu; Ma**, 2024; **Alemany *et al.***, 2023). The digital divide, infrastructure, and teacher preparation continue to hinder the full efficacy of information and communication technology (ICT) in education, despite its well-established benefits (**Wang *et al.***, 2023b). To achieve the long-term educational transformation of ICT, these deficiencies must be addressed.

Cognitive understanding and awareness of AI concepts, procedures, and workplace installations when we talk about AI knowledge and understanding (**Chiu *et al.***, 2023). AI auto-efficacy is an employee's confidence in their AI technological skills. Bandura's self-efficacy hypothesis states that people's motivation and action depend on their perceived ability to succeed (**Lérias *et al.***, 2024). Knowledge and understanding of artificial intelligence includes its technical aspects and real-world applications for increasing decision-making and operational efficiency (**Marin; Nilă**, 2021). When employees are confident in their AI tool use and understand AI principles, their AI self-efficacy increases. Employees must comprehend how AI can improve operations, evaluate data, and deliver predictive insights to use AI effectively (**Almeida; Moreira**, 2022). Empirical research shows that learning boosts self-efficacy in many scientific fields, especially in developing technologies like artificial intelligence. Research shows that training and education in artificial intelligence (AI) boosts employee confidence in using these technologies (**Ayanwale *et al.***, 2022). **Hooda *et al.*** (2022) found a substantial association between students' self-efficacy and AI literacy and exposure in school. This implies a similar link in professional situations. **Chatterjee *et al.*** (2023) found that ongoing AI learning and engagement improves employee technical self-efficacy, enabling them to perform AI-driven jobs more efficiently (**Akour *et al.***, 2021). These findings emphasise the importance of knowing how artificial intelligence affects self-efficacy, especially as AI is increasingly integrated into daily jobs. Empirical study shows that employees who comprehend AI have higher AI self-efficacy (**Almaiah *et al.***, 2022). Employees' self-efficacy improves as they become more comfortable and proficient with AI technologies. Because mastering experiences affects self-efficacy, employees' confidence in their AI skills increases as they are exposed to AI principles and their practical applications (**Al-Maroof *et al.***, 2022); this boosts AI self-efficacy. Cognitive mastery of AI tools may reduce fear and opposition to AI integration, increasing productivity (**Flavián *et al.***, 2022). Theoretical and empirical evidence suggest that employees' AI knowledge and understanding will affect their AI self-efficacy.

H1: Knowing and understanding AI significantly influences the employees AI auto-efficacy.

Empirical research has shown a strong correlation between AI understanding and use. The Technology Acceptance Model (TAM) states that technology adoption is heavily influenced by its perceived simplicity and utility (**Liao; Sundar**, 2022). Research demonstrates that people who grasp AI ideas and applications are more inclined to value and use AI professionally. **Lee *et al.*** (2021) discovered that understanding a new technology reduces ambiguity and fear, enhancing employee adoption. **Ozturk *et al.*** (2023) discovered that workers' preparedness to embrace AI is positively connected with their faith in its productivity and decision-making benefits. Research shows AI skill reduces technology reluctance. Lack of information or employment concerns may prevent adoption of new technology. Employees like AI more when they grasp its potential and limitations. **Kim and Lee** (2024) found that technological familiarity reduces resistance to modern technology and improves comprehension. According to **Mohr and Kühl** (2021), knowing AI considerably increases the likelihood of participating in AI-related activities. Learning about AI helps employees see it as a tool they can master, which increases their readiness to use it in their work (**Almarzouqi *et al.***, 2022). Understanding AI's practical ramifications and benefits can lessen job displacement anxieties and raise the possibility of seeing AI as an enabler rather than a disruptor. Knowledge-driven perception shifts support TAM's claim that perceived ease of use and usefulness shape behavioural intentions (**Wang *et al.***, 2023b). Knowledge is crucial to AI technology adoption because employees' behavioural desire to use it increases as they learn more about it.

H2: Knowing and understanding AI significantly influences the employee’s behavioral intention.

Knowledge acquisition and ICT learning have long been linked empirically. Studies show that employees' knowledge of new technologies like AI improves their ability to use other ICT tools, producing a positive feedback loop (**Candini *et al.***, 2023). **Steels** (2022) observed that employees skilled in emerging technologies are more flexible to learning new ICT applications because their fundamental technical knowledge decreases the learning curve for succeeding technologies. According to **Al-Hamad *et al.*** (2021), understanding AI concepts like machine learning and data analytics positively correlates with an employee's ability to engage with various ICT platforms, suggesting that AI knowledge accelerates

ICT learning by equipping employees with the skills to navigate complex technological environments (**Andrews *et al.***, 2021). AI knowledge leads to technology literacy and proactive ICT learning. Other empirical research has shown that AI and ICT learning complement each other. For instance, **Song *et al.*** (2022) explored how AI-driven systems are able to automate tasks, provide learning paths, and give immediate feedback that can guide employees in learning ICT skills much faster. **Jiang *et al.*** (2022) stated that AI-savvy staff can use AI-enhanced features to personalize and optimize digital learning platforms for ICT learning. In the context of AI and ICT learning, which is increasingly getting interrelated, these empirical findings indicate a significant relationship between knowledge of AI and employee engagement with ICT learning (**Wang *et al.***, 2021). Indeed, this empirical demonstration is a good indication that the knowledge and understanding of AI may strongly impel the employee's ICT learning. Employees who are well conversant with AI can adopt the new ICT system once AI gets integrated into the ICT tools and platforms (**Kelly *et al.***, 2023). This understanding gives workers the confidence to learn ICT since AI can contribute to problem-solving and finding new features. The concepts of AI, such as automation and data analysis, give means for the workers to situate their learning of ICT into real-world applications-a more relevant and effective way of learning (**Jang *et al.***, 2021). In this way, AI knowledge enhances ICT learning and helps workers integrate new technologies into their skill set. Knowing and understanding AI may improve the engagement of employees in ICT learning and boost the individual and organisational level in digital transformation.

H3: Knowing and understanding AI significantly influences the employee's information and communication technology learning.

The information source factoring into the employees' comprehension and attitude toward a new technology, AI, is demonstrated in empirical research (**Wang *et al.***, 2023a). Information sources' credibility, relevance, and accessibility influence their acquisition of knowledge about AI and its application. **Aggarwal *et al.*** (2023) showed that reliable and authoritative sources of information bear more on technological acceptability and efficacy than informal or unverified sources. **Al-Rahmi *et al.*** (2021) found that formal channels, like training programs and consultations with experts, enhance the understanding of new technologies and build technology self-efficacy (**Sayaf *et al.***, 2021). The findings perhaps mean that the source of information about AI is relevant to how well employees internalize their concepts of AI and perceived competence in using AI technologies. As shown, more empirical findings indicate that source of information affects AI knowledge and auto-efficacy. **Singh *et al.*** (2021) found that technological efficacy perceptions by employees are more influenced by extensive training, formal schooling, or generally authoritative people rather than peer interaction or social media. Expert-led training strengthens the AI self-efficacy of employees (**Liu; Ma**, 2024). Official and expert-driven sources make the relationship between AI knowledge and auto-efficacy strong. The sources which are informal or untrustworthy weaken the relationship or distort it. These findings establish evidence that source of information is a strong moderator for AI knowledge and auto-efficacy (**Chiu *et al.***, 2023). Formal training programs, business leaders, and scholarly publications strengthen employee AI auto-efficacy. The sources have in-depth information and build employee AI confidence. Informal or inaccurate information may be incomplete, misleading, or not detailed enough; this weakens the relationship between AI knowledge and auto-efficacy (**Seo *et al.***, 2021). Thus, source of information is a moderator for the influence of AI knowledge on employee's auto-efficacy and, therefore, a critical variable in workplace technology confidence.

H4: Source of information significantly moderates the relationship of knowing and understanding AI, and AI auto-efficacy.

Empirical investigations on the sources of information, as emphasized by **Lérias *et al.*** (2024), influence learning and actual use, especially in the case of ICT. **Steels** (2022) posited that workers who learned about AI through industrial experts, professional trainers, or academic literature fared better in terms of progress in using the service within ICT-the content on those sites being immense and well-structured (**Ayanwale *et al.***, 2022). Structured artificial intelligence education, such as professional development programs or institutionalized training, enhances long-term retention, skill progression, and deep participation in the ideas of ICT. The findings of **Song *et al.*** (2022) state that this relation is governed by sources of information which are trustworthy and well-organized, hence enhancing AI and ICT learning (**Akour *et al.***, 2021). These findings show that a source of information moderates AI knowledge and ICT learning. They get more accurate, complete, and relevant knowledge that enhances their learning of ICT when the information is reliable, structured, and driven by experts in AI sources (**Kelly *et al.***, 2023). Information from artificial intelligence sources that are uncredible-for example, from friends, classmates, or social media-may be shallow in terms of depth and imprecise to aid effective learning (**Flavián *et al.***, 2022). The source of information either increases or decreases the artificial intelligence knowledge influence on information and communication technology learning outcomes, changing the learning process and professional technology learning efficacy.

H5: Source of information significantly moderates the relationship of knowing and understanding AI, and information and communication technology learning.

In the context of AI, several studies have maintained that the nature of the intentions of employees, shaped through their knowledge and perception of the AI, remains one of the vital factors influencing how well they would engage with AI tools (**Seo *et al.***, 2021). Therein, from the studies that are based on the Theory of Planned Behaviour and the Technology Acceptance Model, it becomes evident that behavioral intention acts like a bridge between knowledge and actual use of new technologies such as AI (**Ozturk *et al.***, 2023). Therefore, it has been identified from empirical investigations that individuals who possess a high degree of AI knowledge are more likely to form positive behavioral intentions toward the use of the technology, which in turn enhances perceived self-efficacy in use, as explored by **Candini *et al.*** (2023). These findings do point out the intervening role of behavioral intention between the understanding of AI and the capability to confidently use it in workplace contexts (**Almeida; Moreira**, 2022). Building on these findings, the hypothesis has been that behavioral intention significantly mediates the relationship between knowing and understanding of AI and AI self-efficacy. It assumes that the more an employee understands about AI, the stronger his or her intentions to use it effectively, hence being confident in his or her ability to operate AI tools, which is termed AI self-efficacy (**Andrews *et al.***, 2021). The relationship between knowledge, behavioral intention, and auto-efficacy is combined under those very theories, which suggest that cognitive knowledge enables motivational aspects, which in turn further enhance self-efficacy in practical use. According to **Chatterjee *et al.*** (2023), when employees have a good understanding of AI, they tend not only to be more interested in integrating it into their jobs but also in believing in their capability to use it effectively. The said sequence illustrates that knowledge is translated into a de facto belief through the intervening role of behavioral intention for motivating AI auto-efficacy (**Wang *et al.***, 2021). Thus, the hypothesis is that,

H6: Behavioral intention significantly mediates the relationship of knowing and understanding AI, and AI auto-efficacy.

Empirical technology adoption studies like that by **Wang *et al.*** (2023a) show a precept that persons with strong behavioral intention to adopt new technologies drive themselves to learn the relevant information, hence improving their learning outcomes. According to **Lee *et al.*** (2021), active studying of new technologies enhances ICT learning and aptitude. This calls for the need of AI knowledge to translate the AI learning intentions to success. As employees do not possess these digital tool capabilities, then behavioural intention and desire alone may not be sufficient in the absence of a good understanding of AI to support effective ICT learning (**Liu; Ma**, 2024). It is for this reason that AI knowledge and understanding bridge the gap between desiring and actually learning, making it crucial to enhancing ICT learning outcomes.

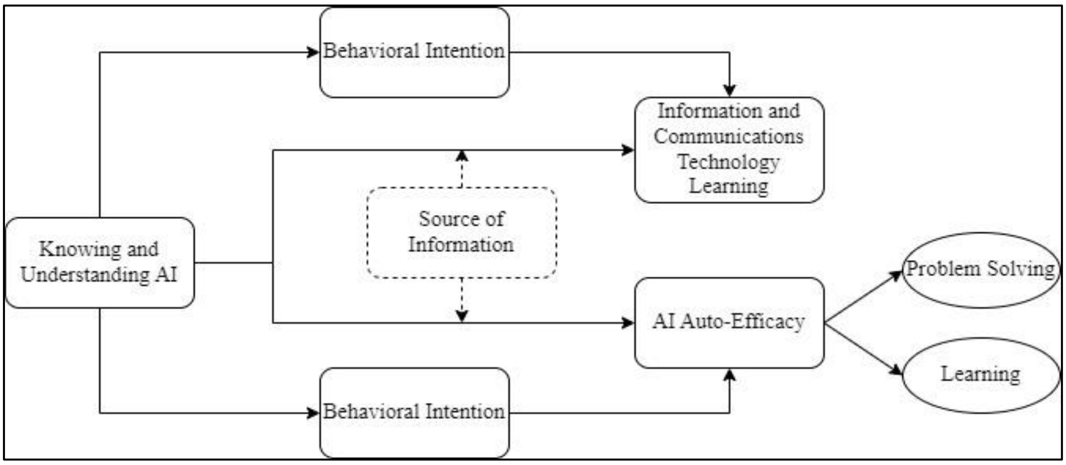

Figure 1: Conceptual Model of Research.

Previous empirical studies have found consistent evidence for the notion that behavioral intention is a very critical driver in the adoption and learning of new technologies, in general, and in the context of ICT (**Al-Maroof *et al.***, 2022). Theory based studies (**Wang *et al.***, 2023a) include the Technology Acceptance Model, which provide insight that persons who have a high level of behavioral intention to use technology are more likely to engage in learning processes that enhance their skill and proficiency. Indeed, investigations have shown that when employees are knowledgeable concerning a specific technology, for example, AI, then the intention to use such technology directly influences engagement in learning efforts related to ICT (**Lee *et al.***, 2021). **Al-Rahmi *et al.*** (2021) finds that more the knowledge of AI, the more positive the attitude toward such technology and the stronger the intention to learn with the purpose of mastering communication technologies related to it. In other words, when employees understand AI's capabilities and the potential application of the technology in their environment, they are most likely to form positive intentions toward using it, hence being more involved in ICT learning processes (**Mohr; Kühl**, 2021). This implies that the mediating role of behavioral intention expresses a motivational mechanism where it is the understanding of a technology that would stir the intention to use it and, further, the desire to learn more about it (**Liu; Ma**, 2024). Hence, the hypothesis is that there is an intervening role played by behavioral intention, which will translate AI knowledge into specific learning outcomes in the ICT domain, enabling not only the use of AI but also improving the larger technological learning and capability (**Wang *et al.***, 2023b).

H7: Behavioral intention significantly mediates the relationship of knowing and understanding AI, and information & communication technology learning.

3. Methodology

This study examined how AI knowledge and understanding affect employee results in Saudi Arabian software companies. PLS-SEM was used to analyse data from the quantitative investigation. The research included 289 software industry personnel from various firms to ensure a wide representation of AI technology experiences and viewpoints. A standardised questionnaire was given to selected participants to collect data. The questionnaire was carefully constructed to measure AI knowledge, auto-efficacy, behavioural intention, and ICT learning. The questionnaire scales were based on previous research to assure validity and reliability. Each scale was carefully chosen based on its usefulness in past studies and adapted to software houses. On a Likert-type scale, participants could rate their agreement or disagreement with comments on the constructs of interest.

Table 1: Instruments of the Research.

No	Variable of the Study	Items	Reference Study
1	Knowing and Understanding AI	05	(**Zhao *et al.***, 2022)
2	Behavioral Intention	03	(**Zhou *et al.***, 2024)
3	Source of Information	06	(**Broadbent *et al.***, 2019)
4	AI Auto-Efficacy	06	(**Lérias *et al.***, 2024)
5	Information and Communication Technology Learning	07	(**Mills *et al.***, 2015)

This study chose PLS-SEM for its capacity to handle complex models with numerous components and reflecting indicators. The study examined how AI knowledge affects auto-efficacy, behavioural intention, and ICT learning. The PLS-SEM method assessed the measurement model and structural model, revealing construct validity, reliability, and hypothesised relationship strength and significance. The measurement model was tested for internal consistency, convergent validity, and discriminant validity, while the structural model was tested for path coefficients and model fit. This strategy gave a complete picture of how AI knowledge affects employee outcomes and permitted precise hypothesis testing.

4. Results

Table 2 shows the study's constructs' Cronbach's Alpha coefficients, assessing scale internal consistency and reliability. Many scales utilise Cronbach's Alpha to determine how effectively their items measure the same concept. Higher values suggest more reliability. AI Auto-Efficacy has 0.750 Cronbach's Alpha. This result indicates good internal consistency for the scale assessing employees' AI technology confidence. AI auto-efficacy is consistently assessed by items in this scale with an alpha value above 0.70. Behavioural Intention has 0.758 Cronbach's Alpha. This coefficient demonstrates that the scale used to measure employees' AI adoption aspirations is trustworthy and consistent. A somewhat higher alpha value indicates that the scale accurately measures participants' readiness and motivation to use AI tools. Information and Communication Technology Learning has a remarkable 0.923 Cronbach's Alpha. This very high result indicates great internal consistency for the ICT learning scale. A high alpha shows that the items are tightly connected and measure employees' comprehensive ICT learning.

Table 2: Cronbach Alpha.

	Cronbach's Alpha
AI Auto-Efficacy	0.750
Behavioral Intention	0.758
Information and Communication Technology Learning	0.923
Knowing and Understanding AI	0.806
Learning	0.779
Problem Solving	0.746
Source of Information	0.752

Knowing and Understanding AI has 0.806 Cronbach's Alpha. This high coefficient shows the scale assessing employees' AI knowledge and understanding is reliable. This scale's good alpha value shows that it accurately measures employees' AI understanding. Learning has 0.779 Cronbach's Alpha. This result indicates strong internal consistency for the AI and ICT general learning outcomes scale. An alpha above 0.70 suggests that the scale accurately measures employee learning. Problem Solving has 0.746 Cronbach's Alpha. This result shows good internal consistency for the AI and ICT problem-solving scale. The alpha value implies the items accurately measure employees' technological problem-solving ability. Source of Information has 0.752 Cronbach's Alpha. The scale quantifying the impact and legitimacy of information sources on AI knowledge is reliable based on this coefficient. An alpha above 0.70 suggests that the scale consistently assesses how diverse sources of information affect employees' AI understanding.

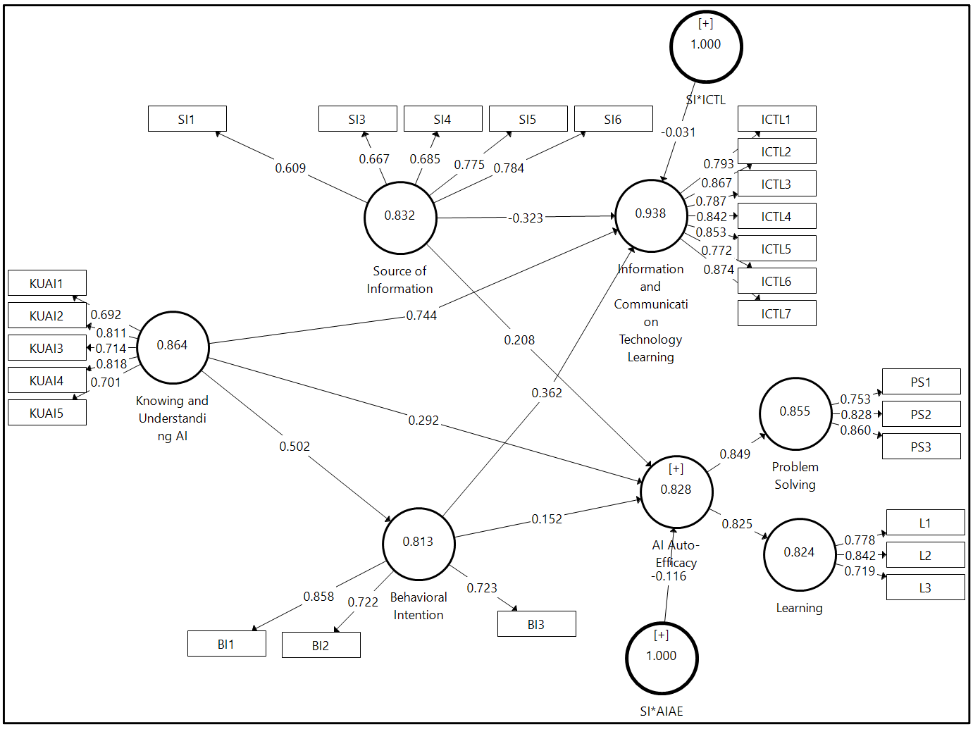

Figure 2: Estimated Model.

Table 3 shows scale fitness statistics for the study's constructs, including original sample factor loadings, composite reliability, and AVE values. Original sample factor loading ranges from 0.722 to 0.858 on the Behavioural Intention scale, with composite reliability of 0.813 and AVE of 0.593. These scores indicate that the scale is moderately dependable and explains construct variance well. The Information and Communication Technology Learning scale has high factor loadings of 0.772 to 0.874, composite reliability of 0.938, and AVE of 0.685, indicating significant reliability and explanatory power for ICT learning. The Knowing and Understanding AI scale has factor loadings between 0.692 and 0.818, composite reliability of 0.864, and AVE of 0.561, indicating good reliability and variance extraction. Factor loadings range from 0.609 to 0.784 on the Source of Information scale, with a composite reliability of 0.832 and an AVE of 0.500, showing acceptable reliability but space for variance extraction improvement. Good reliability and modest variance extraction characterise the AI Auto-Efficacy scale's composite reliability of 0.828 and AVE of 0.547. The Learning scale has factor loadings between 0.719 and 0.842, composite reliability of 0.824, and AVE of 0.610, indicating good reliability and variance explained. Last, the Problem Solving scale has factor loadings from 0.753 to 0.860, composite reliability of 0.855, and AVE of 0.664, demonstrating good reliability and strong explanatory power for problem-solving abilities. The scales differ in reliability and variance extraction, but most contain robust measurement features.

Table 3: Scales Fitness Statistics.

	Factor	Original Sample	Composite Reliability	Average Variance Extracted (AVE)
Behavioral Intention	BI1	0.858	**0.813**	**0.593**
	BI2	0.722		
	BI3	0.723		
Information and Communication Technology Learning	ICTL1	0.793	**0.938**	**0.685**
	ICTL2	0.867		
	ICTL3	0.787		
	ICTL4	0.842		
	ICTL5	0.853		
	ICTL6	0.772		
	ICTL7	0.874		
Knowing and Understanding AI	KUAI1	0.692	**0.864**	**0.561**
	KUAI2	0.811		
	KUAI3	0.714		
	KUAI4	0.818		
	KUAI5	0.701		
Source of Information	SI1	0.609	**0.832**	**0.500**
	SI2	0.667		
	SI3	0.685		
	SI4	0.775		
	SI5	0.784		
AI Auto-Efficacy			**0.828**	**0.547**
Learning	L1	0.778	**0.824**	**0.610**
	L2	0.842		
	L3	0.719		
Problem Solving	PS1	0.753	**0.855**	**0.664**
	PS2	0.828		
	PS3	0.860		

Table 4 shows the Fornell-Larcker criterion values used to evaluate discriminant validity among study constructs. The diagonal values in the table show the square root of the average variance extracted (AVE) for each construct, whereas the off-diagonal values show construct correlations. The AI Auto-Efficacy construct has an AVE square root of 0.668, confirming its uniqueness and variance capture. The AVE square root of Behavioural Intention is larger than its correlations with other variables, indicating good discriminant validity. The Information and Communication Technology Learning construct has the greatest AVE square root of 0.828, indicating good differentiation. The AVE square root of 0.749 for Knowing and Understanding AI is higher than its correlations with other variables, demonstrating discriminant validity. With an AVE square root of 0.707, the Source of Information concept has good discriminant validity because its value is bigger than its correlations with other constructs. The Fornell-Larcker criterion shows that each concept is distinct, validating the study's measuring model.

Table 4: Fornell-Larcker Criterion.

	1	2	3	4	5
AI Auto-Efficacy	0.668				
Behavioral Intention	0.595	0.770			
Information and Communication Technology Learning	0.574	0.581	0.828		
Knowing and Understanding AI	0.681	0.502	0.807	0.749	
Source of Information	0.615	0.618	0.341	0.536	0.707

The Heterotrait-Monotrait Ratio (HTMT) criterion values in Table 5 establish discriminant validity by assessing construct differentiation. The HTMT values compare average correlations between items from different constructions to those from the same construct. AI Auto-Efficacy has high correlations with Behavioural Intention (0.848) and Knowing and Understanding AI (0.873), but lower correlations with Information and Communication Technology Learning (0.690) and Source of Information (0.785). Behavioural Intention interacts strongly with AI Auto-Efficacy (0.848) and Source of Information (0.854) and moderately with Information and Communication Technology Learning (0.727) and Knowing and Understanding AI (0.649). Information and Communication Technology Learning has high HTMT scores for Knowing and Understanding AI (0.874) and moderate for AI Auto Efficacy. Finally, Knowing and Understanding AI has high HTMT values for AI Auto-Efficacy (0.873) and Information and Communication Technology Learning (0.874), although its connection with Source of Information (0.667) is lower but still significant. HTMT values show that while some dimensions, like AI knowledge and learning outcomes, have strong connections, all constructs have adequate discriminant validity, demonstrating that the model's constructs are different.

Table 5: HTMT Criterion.

	1	2	3	4	5
AI Auto-Efficacy					
Behavioral Intention	**0.848**				
Information and Communication Technology Learning	**0.690**	**0.727**			
Knowing and Understanding AI	0.873	**0.649**	0.874		
Source of Information	**0.785**	0.854	**0.394**	**0.667**	

Table 6 displays model goodness of fit measures, such as Q²_predict, RMSE, and MAE, used to assess model correctness and predictive performance. The Q²_predict value of 0.595 shows high predictive relevance, indicating the model accurately captures observed data variation. Higher numbers indicate better model prediction. The average size of the errors between predicted and actual values is 0.064. A lower RMSE indicates better model fit. The RMSE implies that the model predictions are close to the observed values, confirming its precision. The MAE value of 0.082 measures the average absolute error between predicted and actual values. Lower MAE values indicate better model fit. The model's MAE of 0.082 confirms its data prediction accuracy. Table 6's goodness of fit statistics demonstrate the model's predictive power and data alignment.

Table 6: Model Goodness of Fit Statistics.

Q^2predict	RMSE	MAE
0.595	0.064	0.082

Table 7 shows R-square and F-square statistics for model constructs, revealing explained variance and predictor variable effect sizes. The R-square values show the proportion of variance explained by the model for each dependent variable, while the R-square Adjusted values account for predictors and quantify model fit more accurately. The corrected R-square for AI Auto Efficacy is 0.607, indicating that the model explains 61% of the variance in AI Auto Efficacy. The predictors and AI auto-efficacy appear to be strongly correlated. The R-square value for Behavioural Intention is 0.252 and the adjusted R-square value is 0.250, indicating a moderate amount of explained variance. The F-square value of 0.272 indicates a moderate effect size. Information and Communication Technology Learning has a high R-square value of 0.749 and an adjusted R-square of 0.746, indicating that the model explains a lot of ICT learning variance. Knowing and Understanding AI has moderate explanatory power compared to other factors with an R-square of 0.100 and an adjusted R-square of 0.338. Learning and Problem Solving had strong R-square values of 0.681 and 0.720, respectively, with adjusted R-square values of 0.680 and 0.720, indicating significant explanatory power and effect sizes. F-square statistics show that predictors affect each construct, with values of 2.137 and 2.576 for AI Auto-Efficacy and moderate values for other constructs, indicating different effect sizes and predictor importance in explaining outcome variance. Table 7 shows how well the model captures variance across constructs and how predictor factors affect dependent variables.

Table 7: R-Square and F-Square Statistics.

	R Square	R Square Adjusted	AI Auto-Efficacy	Behavioral Intention	Information and Communication Technology Learning	Learning	Problem Solving
AI Auto-Efficacy	0.612	0.607				2.137	2.576
Behavioral Intention	0.252	0.250	0.031		0.272		
Information and Communication Technology Learning	0.749	0.746					
Knowing and Understanding AI			0.100	0.338	1.007		
Learning	0.681	0.680					
Problem Solving	0.720	0.720					
SI*AIAE			0.080				
SI*ICTL					0.009		
Source of Information			0.061		0.224		

Path analysis, which investigates model constructs' direct, moderating, and mediating impacts, is shown in Table 8. The Knowing and Understanding AI -> AI Auto-Efficacy path has an original sample coefficient of 0.292, a standard deviation of 0.103, a t-statistic of 2.825, and a p-value of 0.002. The statistically significant beneficial association between employees' AI understanding and AI technology self-efficacy is shown. The positive coefficient shows that employees' AI expertise and trust in utilising AI tools rises dramatically. From Knowing and Understanding AI to Behavioural Intention, the original sample coefficient is 0.502, the standard deviation is 0.076, the t-statistic is 6.645, and the p-value is 0.000. AI knowledge positively and statistically affects employees' intentions to adopt AI technologies. This suggests that AI knowledge motivates and engages personnel with AI tools. According to the route Knowing and Understanding AI -> Information and Communication Technology Learning, the original sample coefficient is 0.744, the standard deviation is 0.051, the t-statistic is 14.622, and the p-value is 0.000. This shows that a stronger grasp of AI considerably improves employee ICT learning.

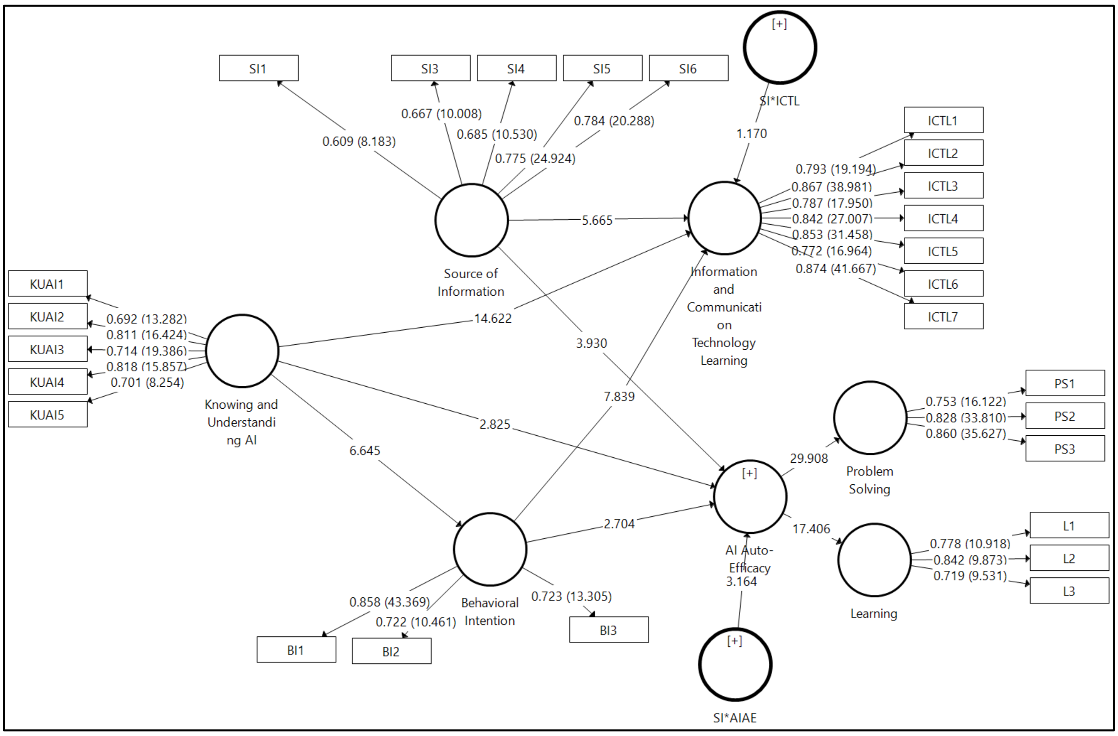

Figure 3: Structural Model for Path Analysis.

The source of information moderates Knowing and Understanding AI -> AI Auto-Efficacy (SIAIAE) with a coefficient of -0.116, standard deviation of 0.037, t-statistic of 3.164, and p-value of 0.001. This shows that information quality moderates the connection between AI knowledge and auto-efficacy. The moderation effect of the source of information on Knowing and Understanding AI -> Information and Communication Technology Learning (SIICTL) is not statistically significant with a coefficient of -0.031, a standard deviation of 0.027, a t-statistic of 1.170, and a p-value of 0.121. Finally, the mediated routes demonstrate Knowing and Understanding AI -> Behavioural Intention -> AI Auto-Efficacy with an original sample coefficient of 0.076, standard deviation of 0.032, t-statistic of 2.402, and p-value of 0.008. Behavioural intention appears to mediate the AI knowledge-auto-efficacy relationship. The mediated path Knowing and

Understanding AI -> Behavioural Intention -> Information and Communication Technology Learning has a coefficient of 0.182, a standard deviation of 0.040, a t-statistic of 4.571, and a p-value of 0.000, indicating that behavioural intention enhances AI knowledge's effect on ICT learning. These findings demonstrate the importance of direct, moderating, and mediating influences in understanding AI knowledge and technological outcomes.

Table 8: Path Analysis

	Original Sample (O)	Standard Deviation (STDEV)	T Statistics (O/STDEV)	P Values
Knowing and Understanding AI -> AI Auto-Efficacy	0.292	0.103	2.825	**0.002**
Knowing and Understanding AI -> Behavioral Intention	0.502	0.076	6.645	**0.000**
Knowing and Understanding AI -> Information and Communication Technology Learning	0.744	0.051	14.622	**0.000**
SI*AIAE -> AI Auto-Efficacy	-0.116	0.037	3.164	**0.001**
SI*ICTL -> Information and Communication Technology Learning	-0.031	0.027	1.170	**0.121**
Knowing and Understanding AI -> Behavioral Intention -> AI Auto-Efficacy	0.076	0.032	2.402	**0.008**
Knowing and Understanding AI -> Behavioral Intention -> Information and Communication Technology Learning	0.182	0.040	4.571	**0.000**

5. Discussion

While companies nowadays have started embracing Artificial Intelligence in their businesses, the interactions between expertise in AI and technical capabilities become very important. This paper, therefore, investigates the complex interrelations among employees' AI comprehension, self-efficacy, behavioural intention, and ICT learning outcomes. It looks at how AI knowledge affects employees' technical behavior and learning. This paper explores how knowledge of AI influences auto-efficacy and the adoption of technology by analyzing the moderating and mediating functions of the source of information. The results reveal how knowledge of AI can enhance ICT self-efficacy and competence, and also the quality of information as an important determinant of outcome. The session will discuss how firms may exploit knowledge of AI in training personnel in digital technology. This analysis will present these insights through an examination of the relationships between these variables.

The confirmation of the initial hypothesis, which held that employees' AI self-efficacy is greatly impacted by their knowledge and understanding of AI, highlights the importance of knowledge acquisition in boosting employees' confidence and self-confidence in using AI technology. This study supports self-efficacy theory, which highlights cognitive comprehension's role in self-evaluating. People who understand AI concepts are more confident in their capacity to use AI technologies, which boosts self-efficacy. Technical competence can boost a person's confidence in their technological skills (**Al-Rahmi *et al.***, 2021). A thorough understanding of artificial intelligence reduces employees' nervousness and gives them the skills to use AI technologies. This self-efficacy should lead to more efficient AI utilisation as AI is integrated into varied company activities. As AI integrates, humans will feel more confident in their ability to negotiate difficult AI-driven tasks. Companies that invest in AI education are more likely to develop a workforce with both knowledge and skill. Thus, productivity and innovation may increase.

The second hypothesis, which explored the relationship between employees' AI knowledge and their willingness to use AI, was likewise supported, confirming that employees' AI knowledge strongly influences their AI tool use. This supports the Technology Acceptance Model (TAM), which states that a technology's perceived ease of use and usefulness determine its adoption (**Kelly *et al.***, 2023). Both aspects are affected by knowledge. Workers who understand artificial intelligence (AI) are more likely to see it as beneficial and less daunting, which motivates them to use it. Behavioural intention mediates the relationship between knowledge and technology use, according to empirical studies like **Almaiah *et al.*** (2022). This investigation shows that knowledge acquisition is vital to promoting AI adoption. The results show that organisations using AI-driven solutions must guarantee their staff understand AI principles. Thus, this will increase their desire to use these technologies. Employees' positive behaviour intentions increase with their understanding of AI's benefits and applications. This makes technological integration easier and more acceptable.

Another hypothesis on how AI knowledge affects ICT acquisition supports the idea that AI knowledge is necessary to learn other technologies. Research shows that AI-savvy workers learn ICT more actively. Understanding AI is crucial to mastering AI-related digital tools and technology. **Wang *et al.*** (2023a) found that various ICT industries apply AI knowledge, supporting the discovery. Understanding AI's fundamentals lets people apply cognitive frameworks to other ICT domains. ICT learning is improved by AI, suggesting it can promote digital literacy. AI language expertise may help employees learn and adapt to ICT platforms. Because companies employ more networked digital technologies. This hypothesis confirms that businesses should adopt AI education and training programs that develop AI competencies. These workshops teach employees about ICT and how to adapt to digital developments in various work settings.

Accepting the fourth hypothesis, which states that information sources greatly influence the relationship between AI knowledge and comprehension and AI self-efficacy, reveals how information sources affect employees' AI technology confidence. As crucial as information volume is AI information source quality and validity. Rigorous training programs, scientific publications, and industry experts provide more accurate and complete knowledge than informal or peergenerated sources (**Kelly *et al.***, 2023). The study also found that AI professionals learn better from respectable sources and tend to be more confident. Professional sources deliver information in a structured manner and, therefore, clearly, limiting confusion and improving communication and understanding. In contrast, incomprehensive knowledge or misunderstandings from less reliable sources could lead to lower levels of self-efficacy. In this regard, the moderating influence underlines that AI training should consider the quality at which the information is being delivered. This will be crucial for establishing employees' trust and technological adoption. With well-directed and reliable information, the company can enhance employee autonomy and, therefore, make the integration of AI smoother.

The fifth hypothesis, exploring how information sources narrow the gap between AI knowledge and understanding, and the results of learning about ICT were accepted. Based on the results, it proved that the quality of the information does make a difference in technology learning outcomes. Research reveals that information origin influences how successfully people apply their knowledge to diverse learning situations (**Chatterjee *et al.***, 2023). This conclusion supports prior research emphasising information source relevance. AI learners from reliable and well-organised sources are better prepared to apply it to other IT education fields. These sites provide detailed, contextually relevant knowledge to foster digital literacy. A systematic learning environment or professional vocational program can help apply artificial intelligence skills in many ICT domains. Informal or unreliable sources may provide less detailed or precise information, lowering ICT learning efficiency. To enhance ICT learning, organisations should evaluate their artificial intelligence training materials' content and sources. Companies can assist employees apply AI to various technological difficulties by employing high-quality information sources. It also improves employees' ICT abilities.

The result acceptance of the hypothesis through which behavior intention significantly mediates the relationship between knowing and understanding AI and AI auto-efficacy underlines the role of intention in translating knowledge into confidence in the usage of AI. This result also corroborates extant literature that has established the roles of behavioral intention in technology adoption and self-efficacy development. This will generate positive intentions to use AI in individuals with high AI knowledge and hence enhance their self-efficacy or confidence level in using AI. This view is underpinned by the mediating role of behavioral intention, which indicates that knowledge in itself is not enough to enhance one's self-efficacy; rather, it is the intention to use AI which provides the motivating force for enhancing one's confidence in AI. Such findings are supported by theories such as Bandura's social cognitive theory, where motivation, as considered within the bounds of behavioral intention, influences belief in one's ability to fulfill or perform a certain task (**Andrews *et al.***, 2021). The significant mediation effect herein reported underlines the necessity for organizations to focus their efforts not only on the improvement of employees' knowledge about AI but also on the creation of positive behavioral intentions through focused interventions, such as AI-centered training programs which enhance both the understanding and motivation of employees.

The same is reconfirmed by the acceptance of the hypothesis that the degree to which behavioral intention mediates in the relationship between knowing and understanding AI and information & communication technology learning further puts into light the critical influence of behavioral intention on the outcome of learning. A good understanding of AI among employees makes them develop an intention to use AI-related tools; then, this will lead to deeper involvement in learning activities involving information and communication technology. The finding points to the fact that knowledge of AI fuels a desire to know more about related technologies and the key mechanism underlying this process is behavioral intention. In this respect, behavioral intention plays a mediating role in the transformation of knowledge about AI into proactive attitudes toward ICT learning and new technological skills and competencies development. These findings are in line with the literature that, according to **Liu and Ma** (2024), point out the motivational role of behavioral intention in learning. This finding implies that, from an organizational perspective, placing emphasis on the creation of environments supportive of improving AI knowledge will also encourage employees' intentions to use and learn about AI, thus becoming effective in ICT learning.

The research shows that all seven assumptions are accepted, demonstrating that AI knowledge affects employees' technical actions and learning results. Understanding artificial intelligence boosts self-efficacy, behavioural goals, and information and communication technology expertise. The moderating contributions of information sources show that AI knowledge sources' quality and authenticity greatly impact this study's results. These results underline the importance of rigorous artificial intelligence education and careful knowledge source selection in creating a technologically capable and confident workforce. Addressing these difficulties will help organisations handle AI's complexity. This will ensure that their personnel enthusiastically adopt new technology and have the skills and confidence to succeed in a digital world.

6. Conclusion

The present study has unpacked complex inter-relationships among employee's knowledge and comprehension of artificial intelligence, self-efficacy, behavioural objectives, and learning outcomes in ICT. Predictably, it has therefore emerged that the development of knowledge about AI would enhance one's self-confidence to use the AI technologies, a desire to use it, and involvement in ICT learning. Scientific evidence shows that AI literacy may provide a key role in the acceptance and use of technology, impacting self-efficacy, behavioral intention, and ICT learning. Deep mediating and moderating effects such as the intention to act and the quality of the information source give an example of how knowledge, motivation, and contextual factors are interacting with each other in detail for technology-related outcomes. These findings give a robust foundation for understanding how the acquisition of AI capabilities can improve organizational performance and the engagement of staff with technology. Finally, this present research contributes to adding AI-specific insights into the theoretical and practitioner literature on technological acceptance and adoption. Targeted training programs that enhance AI knowledge, self-efficacy, and behavioral intention are supported from an empirical research perspective. The companies have to invest in reliable sources of information and devise the usage methods that involve artificial intelligence. The research establishes a strong basis for evaluating the influence of AI knowledge and presents novel opportunities for further investigation. Further investigation of longitudinal effects, contextual factors, and AI technology could enhance the explanatory power of these findings. This research aims to enhance the techniques of technology adoption and the integration of artificial intelligence in businesses.

6.1. Implications of the Study

This work improves our theoretical understanding of how AI knowledge and comprehension affect organisational technology. The findings illuminate the intricate relationships between artificial intelligence (AI) knowledge, self-efficacy, behavioural intention, and ICT learning, broadening technology adoption and use theories. Artificial intelligence knowledge boosts self-efficacy and behavioural intention, sustaining and growing the TAM and TPB. This study found that users' confidence in their AI skills and desire to employ these technologies in their jobs grow when they comprehend AI. Integrating artificial intelligence into theoretical frameworks refines and extends core theories by showing how cognitive components of technological comprehension affect behaviour. This study also suggests that the behavioral intention mediates AI knowledge, auto-efficacy, and information and communication technology learning, extending technology adoption theory. The conclusion of this research are that a behavioral purpose influences such interaction in that motivation and the aim constitute a central role at the AI applications. The sources of information that show contextual elements controlling AI knowledge transfer control AI knowledge and auto-efficacy. The nature and reliability of information sources influence how artificial intelligence knowledge impacts users' self-efficacy. More inclusive models may result with contextual features. This present study achieves its purpose by the introduction of AI-specific qualities in models and other variables to affect technology and learning adoption in the theoretical environment.

This, in turn, would have important implications for companies aiming for higher deployment of AI and more employee engagement. The findings are that comprehensive AI training programs enhance employees' self-efficacy and behavioural intention to adopt AI-powered IT. It instills confidence in them and increases their willingness to use the technologies for better productivity and innovation. The analysis also advised organisations to choose AI information sources with care. In addition, organizations should focus their efforts on highly curated and authoritative content since highly trusted sources can greatly impact the relationship between AI knowledge and auto-efficacy. The study also postulates that the linkage of AI knowledge and outcome is mediated by behavioural intention. This infers that increasing employees' intentions to use AI technologies enhances the adoption of technology and learning of ICT. These pragmatic revelations can help organizations develop customized training programs, use information sources selectively, and foster a positive attitude toward AI-a driving force that can maximize workplace AI acceptance and usage.

6.2. Limitations and Future Research Directions

Despite its discoveries, this research has several drawbacks. Cross-sectional data, which shows changeable associations at one time, is a drawback. This temporal limitation limits causal inference and the dynamic character of AI knowledge and its effects on auto-efficacy, behavioural intention, and ICT learning. We need longitudinal studies to examine these variables over time and better understand the underlying mechanisms. The study also focused on AI technology personnel. This context-specific constraint may limit the findings' applicability to other businesses or areas with different technological adoption landscapes or cultural norms. To confirm and generalise these findings, future research should repeat them across sectors and geographies.

Another limitation is construct scope. The study examined several crucial aspects connected to AI knowledge and its impact, however it did not account for organisational culture, leadership styles, cognitive types, or prior technology experience. These additional variables may help explain how AI knowledge affects auto-efficacy and technology adoption. Future studies could also examine how different AI technologies affect different outcomes. Differentiating between general AI literacy and specialised AI applications (e.g., machine learning, natural language processing) may reveal how AI knowledge affects technological engagement and learning. Examination of feedback mechanisms and iterative learning processes in improving AI-related competencies may provide more insights into technology adoption techniques. Addressing these limits and investigating these future research directions will improve our understanding of AI knowledge and organisational results.

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Appendix A

Knowing and Understanding AI

1. I can distinguish between AI-enabled tools and traditional tools used in my workplace.
2. I know where AI applications can assist me in improving work efficiency.
3. I can identify AI technologies in the AI-based products or services used at work.
4. I feel comfortable when using AI-powered products and applications in my daily tasks.
5. I believe employees should actively learn to use intelligent technologies to enhance workplace productivity.

Behavioral Intention

1. I intend to use AI-enhanced tools and applications in the future.
2. I intend to use AI-augmented solutions frequently in my job tasks.
3. I intend to recommend that others in my organization use AI-enhanced tools.

AI Auto-Efficacy

Problem Solving

1. I can rely on my problem-solving skills when facing challenges involving AI technology.
2. I can handle most issues related to AI systems independently and effectively.
3. I can usually solve complex and demanding tasks when working with AI systems well on my own.

Learning

1. I can keep up with the latest advancements in AI technologies used in the workplace.
2. Despite the rapid developments in AI, I can continuously stay updated.
3. Even with the frequent introduction of new AI applications, I manage to remain current with them.

Source of Information

1. Prior knowledge about specific AI technologies or applications.
2. Recommendations from colleagues, friends, or industry peers.
3. Input from technology consultants or AI specialists.
4. Formal information sources (e.g., industry reports, AI-focused websites, expert articles, professional journals).
5. Advertisements and promotional materials about AI tools or services.
6. Hands-on demonstrations or trial versions of AI systems.

Information and Communication Technology Learning

1. The more often I use AI tools at work, the more I enjoy my tasks.
2. The more I engage with AI-based systems at work, the more motivated I feel.
3. I find learning new AI-based technologies and systems interesting.
4. AI technologies provide me with opportunities to learn and apply new skills.
5. I enjoy discovering new AI innovations in the workplace.
6. The more I use AI-based systems, the more confident I feel in my work tasks.
7. Frequent use of AI at work increases my interest in applying new technologies.