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Harnessing Artificial Intelligence for Learning Effectiveness in the Banking Sector: The Mediating Roles of Technological Self-Efficacy and Learning Orientation

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ABSTRACT

The rapid integration of artificial intelligence (AI) technologies within Pakistan's banking sector has significantly transformed workplace dynamics, reshaping employee roles, learning processes, and organizational expectations. Grounded in social cognitive theory (SCT), this study examines the influence of artificial intelligence usage on perceived learning effectiveness (PLE) and their capacity to effectively adapt to such technological changes. This study specifically investigates the mediating roles of technological self-efficacy (TSE) and learning orientation (LO) in this process. Using quantitative research design, data were collected via a structured questionnaire administered to managerial-level employees from various banks. The purpose sampling technique was used to collect the responses. The data were collected from a sample of 348 managers employed in public, commercial, and Islamic banks located in Punjab (e.g., Bahawalpur, Multan, and Lahore), and were subsequently analysed using partial least squares structural equation modelling (PLS-SEM). The findings indicate that AI usage has a positive and statistically significant influence on technological self-efficacy and learning orientation. Likewise, technological self-efficacy and learning orientation have positive impact on perceived learning effectiveness. Furthermore, the relationship between AI usage and perceived learning effectiveness is mediated by two psychological constructs: technological self-efficacy and learning orientation. The findings indicate that the relationship between AI usage and perceived learning effectiveness is contingent upon both technological self-efficacy and learning orientation. These findings provide both theoretical and practical contributions, enriching the existing literature on technology adoption, workplace learning, and self-efficacy theory. Furthermore, this study provides empirically grounded recommendations for managers and organizational leaders operating within technology-intensive industries.

Introduction

Artificial intelligence (AI) is increasingly shaping the banking sector, emerging as a pivotal element in the design and implementation of employee learning and development initiatives (Alsoukini et al., 2025). Through the use of AI-based tools, such as intelligent tutoring systems and adaptive learning management software, employees can receive personalized training experiences, timely feedback, and targeted microlearning units, which collectively enhance engagement and reduce performance time compared to traditional instructional methods (Yusuf et al., 2024). In recent years, artificial intelligence has emerged as a prominent catalyst for technological advancement, contributing significantly to improving global living standards (Abbas Khan et al., 2024). This technological wave is not only transforming organizational processes but also fundamentally reshaping the nature and dynamics of the workplace (Mossavar-Rahmani & Zohuri, 2024).

Due to advancements in artificial intelligence, banks have the capacity to deliver tailored learning solutions, thereby facilitating the development of a more adaptable workforce capable of meeting the evolving demands of the contemporary global economy (Moffett et al., 2024). To remain effective within an increasingly dynamic environment, employees are required to engage in continuous acquisition of new knowledge and the development of advanced competencies. While the integration of artificial intelligence into human workflows may not represent as radical a transformation as often portrayed, it remains essential to pursue ongoing research into its effects on work practices and the processes of learning within professional contexts (Li & Yeo, 2024).

Artificial intelligence usage into the coaching industry has given rise to novel strategies for employee development and the enhancement of organizational productivity (Cascio & Montealegre, 2016). However, the effectiveness of employee learning acts as a driving force, motivating individuals to develop their potential through the acquisition of new skills and knowledge (Ghedabna et al., 2024). Employees with a strong learning goal orientation frequently perceive AI as a valuable resource for enhancing and refining their professional competencies. Their outlook fosters a willingness to engage with AI in addressing complex challenges, thereby enhancing their self-efficacy. Collaboration between employees and artificial intelligence can strengthen employees' confidence, thereby increasing their propensity to engage in learning opportunities and ultimately enhancing their self-efficacy (Chen, Yang, et al., 2023). According to Han et al. (2025), self-efficacy refers to an individual's belief in their capacity to successfully perform tasks and attain desired objectives. These beliefs are significant as they exert a substantial influence on the decision-making process. AI usage can be conceptualized as an emerging environmental factor with the potential to influence individuals' self-efficacy, thereby shaping employees' readiness to engage in risk-taking behaviors.

Over time, scholars have examined various individual characteristics that influence the extent to which individuals place trust in automation. This study has examined factors including individuals' inclination to trust automated systems, their comfort level with technology (Kohn et al., 2021), and their self-efficacy in using technological tools. Furthermore, learning orientation encompasses a set of attributes that reflect an employee's proactive inclination toward acquiring knowledge, including a commitment to personal and professional development, alignment with a collective vision, and the maintenance of an open and receptive mindset. The capacity of an organization to foster a learning culture is largely contingent upon the extent to which it prioritizes and values learning (Bista et al., 2023). Although accompanied by various challenges, AI usage fosters the emergence of new job roles and facilitates opportunities for skill development. Establishing trust necessitates transparency and the development of explainable artificial intelligence systems.

Ultimately, artificial intelligence is transforming the banking sector by enhancing human capabilities, fostering innovation, and enriching the overall employee experience (Robb, 2022).

Although substantial research has been conducted on artificial intelligence and learning, the specific relationship between AI usage and perceived learning effectiveness within the banking sector remains insufficiently explored. Chou et al. (2024) and Pashtranjaku et al. (2024) have acknowledged the role of AI in enhancing operational efficiency; however, they did not examine its potential to strengthen self-efficacy. Likewise, studies by Chishti et al. (2024) and Peng et al. (2022) have investigated this topic, Königstorfer and Thalmann (2022), as well as Bradu et al. (2023) have likewise neglected to address the critical role of perceived learning effectiveness. Notably, the influence of learning orientation in shaping the relationship between AI usage and learning effectiveness has received limited scholarly attention.

In the banking sector, it is imperative to continuously refine and optimize artificial intelligence strategies to ensure alignment with environmental, social, and governance (ESG) goals. Engaging in this discussion may provide insights into how the integration of AI and learning can contribute to advancing sustainability within the industry. The present study is grounded in Bandura (1999) social cognitive theory, which offers a comprehensive framework for understanding how individuals acquire and apply knowledge within a dynamic and evolving context. The proposed theory aligns with the concept of reciprocal determinism, which describes the mutual interdependence among factors such as self-efficacy and motivation, participation in learning activities, and environmental influences, including the integration of AI within the workplace (Shahzad et al., 2022). The study examines the increasing significance of artificial intelligence in improving operational efficiency and securing competitive advantage within Pakistan's banking sector, while addressing a notable gap in the literature regarding the outcomes of AI usage in emerging economies. The primary focus lies in elucidating the relationship between employee learning and effectiveness, alongside the implementation of artificial intelligence. The study examined the mediating roles of technological self-efficacy and learning orientation, providing robust empirical evidence supporting the proposed relationship.

Literature Review and Hypothesis Development

Social Cognitive Theory

SCT introduced by Bandura in 1986, sheds light on learning happens through dynamics interplay of personal belief, behaviors and surroundings environments. A pivoted part of SCT is the concept of self-efficacy, which is essentially a person's confidence in their ability to achieve success in various situations. This belief has a direct impact on motivation, on how we set our goals, and our determination to tackle learning challenges. In the realm of digital learning, technological efficacy and a learner's confidence in using technology become incredibly important. Compeau and Higgins (1995) discovered that employees who have a strong belief in their technological skills are more inclined to engage with and thrive in technology settings. This will especially be important in the banking sector where the employees are required to smoothly maneuver through AI-based applications including fraud detection systems, robot advisors, and predictive navigation tools. It was emphasized by Liaw et al. (2007) that attitude of an individual towards technology and how a person perceives technology to be easy or complex, has a significant influence on the learning of such a person in a technology-intensive setting.

Nonetheless, another difficulty real banks must cope with is the challenge of training their employees to adopt AI in their lives and businesses without paying much attention to their different levels of technological expertise in language and skills. As Roll and Wylie (2016) commented on, although AI can take the form of valuable feedback giving with performances, and creating aids with decision making, success is largely made by engagement and the willingness to incorporate those aspects that highly rest on the principals of the social cognitive theory. Despite this, Holstein et al. (2018) have indicated that with the aid of AI tools employee learning can be improved through offering adaptive, real time feedback to employees during training simulation. Similarly, Chen et al. (2020) discovered that AI propensity toward personalizing learning routes entails better training in the business setting. Nevertheless, notwithstanding these benefits, there is a conspicuous paucity in research studying the direct relationship between AI usage on the long-term learning process in the banking sector (with special focus on those jobs that are not strictly customer service oriented). Zawacki-Richter et al. (2019) supported these statements by recognizing a disconnect between AI-based methodologies and well-established educational theories such as SCT in the workplace. Such inconsistencies highlight the importance of conducting further empirical studies regarding the influences of SCT concepts including self-efficacy and learning orientation of how AI based learning systems can increase success in the banking industry as the industry is currently experiencing the digital transformation revolution in full swing.

Technological Self-Efficacy as a Mediator

According to this model, this approach increases technological self-efficacy since interaction with technology via AI becomes easier and users will be more likely to perceive technology as an ally that helps through adaptive support and automation of tasks. Studies carried out in educational and working environments suggest that AI tools may help their user in critical areas such as improving their perception of their technology use capabilities through providing intra-time feedback, simpler interfaces and help to learn to be better users of the technology in each situation (Al-Rahmi et al., 2022). As an example, technological self-efficacy can be improved with the help of AI driven learning systems and decision-support tools, when the users are sufficiently trained and exposed to them regularly (Weidinger et al., 2024). Nevertheless, the possible issues related to overuse of the AI have been voiced by some of the newly developed studies, and it might result in the loss of confidence in their technological competencies on part of the users (Carr, 2020).

Additionally, the black box nature of AI systems can create issues with transparency and trust, potentially harming technological self-efficacy (Shin, 2021). Despite these insights, there are still significant gaps in research, especially the need for long-term studies that look at how ongoing interaction with AI usage influences technological self-efficacy over time, as well as the lack of exploration into how culture, age-related and industry-specific factors, especially in the banking sector, specific factors play role (Do Nguyen & Nguyen, 2023). There is a lack of research that dives into how AI usage influences technological self-efficacy, especially in the banking sector of Pakistan. This highlights the urgent need for more detailed and diverse studies in this field. Therefore, this research is to propose the following hypothesis:

H1: AI usage is significantly and positively related to technological self-efficacy.

Self-efficacy is a fundamental aspect of how we think and learn, playing a vital role in influencing our behaviour. According to social cognitive theory, individuals with high self-efficacy are more likely to set challenging goals and persist in achieving them (Bandura, 2001). Employees who believe in their capabilities are more inclined to seek out knowledge and skills related to their jobs actively, and they often possess a sense of curiosity and adventure that nurtures innovative thinking (Yang, 2021). In AI-enhanced training systems, such as adaptive e-learning platforms or smart performance support tools, TSE plays a significant role in boosting cognitive engagement, motivation, and performance outcomes (Al-Rahmi et al., 2021). Research suggests that individuals who are confident in their tech abilities are more likely to dive into AI tools and are better at reaping their benefits (Van Dinther et al., 2011).

However, current literature often overlooks specific industries, especially the banking sector, that might influence the relationship between TSE and learning effectiveness. Additionally, most studies focus on students, which may limit the applicability of these findings to a broader range of employees (Tran et al., 2024). Chen, Zhang, et al. (2023) demonstrated that the use of AI significantly enhances innovative behaviours, with self-efficacy acting as a dynamic mediating factor. This research highlights that AI tools boost employee confidence in their abilities, which in turn encourages them to take innovative risks. In a similar vein, Yin et al. (2025) examined the dual effects of AI, which enhances self-efficacy and encourages employees to engage in innovative activities and risk-taking ventures. Furthermore, research by Liang et al. (2024) suggests that medical AI-assisted diagnostic systems indirectly encourage doctors to embrace innovative treatment plans by bolstering their professional confidence. Based on these sights, we propose the following hypotheses:

H2: Technological self-efficacy is positively associated with perceived learning effectiveness.

H3: Technological self-efficacy mediates the relationship between AI usage and perceived learning effectiveness.

Learning Orientation as a Mediator.

Smart learning has the incredible ability to combine digital tools like AI and social media, transforming the learning environments for employees (Allal-Chérif et al., 2021). This shift in learning spaces is evident through personalized and engaging experiences that are enhanced by AI analysis (Kiani, 2024). However, tools powered by AI, like intelligent tutoring systems, chatbots, and recommendation engines, are designed to support self-directed learning and inspire users to see challenges as chances for growth, which helps to strengthen a learning-oriented mindset (Al-Rahmi et al., 2021). Recent research indicates that AI tools boost learners' intrinsic motivation and engagement, two essential elements of a learning-oriented approach (Shin, 2021). However, there are still some gaps in the existing literature. For one, most studies have focused on academic settings rather than workplace environments, which limits how applicable the findings are to organizational learning contexts (Zhang et al., 2022).

Additionally, there is a shortage of longitudinal or experimental research that can demonstrate a causal relationship between AI use and an increase in learning orientation over time. Furthermore, few studies delve into the psychological factors like motivation, receptiveness to feedback, or perceived control that might influence this connection (Pham et al., 2023). Lastly, there's a lack of exploration into cross-cultural and sector-specific differences, as much of the research has centered on Western or technologically advanced populations, leaving a gap in our understanding of how various environments affect the AI-learning orientation relationship (Lin & Lee, 2024). In the banking sector, learning is utilized to increase employee engagement, foster teamwork, support mental well-being, and enhance performance. A key study revealed that smart learning programs have a positive impact on employees' work capacity and mental health. By leveraging AI, we can create vibrant learning environments that inspire and motivate employees. Based on the preceding discussion, this study proposes the following hypothesis.

H4: AI usage is significantly and positively related to learning orientation.

Having a proactive mindset geared towards continuous learning, where one embraces challenges and seeks to expand one's knowledge, has been positively associated with various markers of learning effectiveness. These include improved knowledge acquisition, skill development, and workplace performance (Sahni & Chilton, 2025). Specifically, environments that foster a learning orientation encourage thriving, meaningful work, and proactive behaviors, which are essential for achieving effective learning outcomes (Raza et al., 2018). Nevertheless, it is worth noting that most studies like those conducted by Raza et al. (2023) are cross-sectional, revealing a lack of longitudinal research that sheds light on how learning orientation and effectiveness evolve. While delving into informal learning in AI-enabled workplaces, there is a noticeable lack of context-specific studies across industries, particularly in blue-collar or less formal work settings.

Moreover, we have not really delved into how these factors connect, especially when it connects, especially when it comes to thing like psychological states that promote thriving at work or resilience. Further we still need to pay attention to how team dynamics or overall organizational climate such as the impact of leadership that encourages learning or prevailing culture shapes individual learning success (Mosqueira-Rey et al., 2023). Through this discussion, we could significantly enhance our understanding of how adopting a learning orientation boost learning effectiveness in today's ever-changing work environments. AI acts like a virtual mentor, helping individuals build their self-competence, motivation, and time management skills (Jin et al., 2020). This kind of support can boost learning outcomes. By focusing on learning orientation, we can create personalized education that caters to each person's interests, needs, and abilities (Priamono et al., 2024). In addition, learning orientation also can boost motivation and self-esteem using characteristics that offer incentives and social support (Tack, 2019).

Given this theoretical tie, there is still a sizable void in empirical research that examines learning orientation as a mediator of AI usage to learning outcomes. Likewise, a high number of studies have considered mainly developed , western educational or corporate settings thereby restricting the generalizability of the findings (Luckin & Holmes, 2016). The discrepancies also exist in definition and measurement of learning orientation as some studies are directed at individual traits and other ones are determined on organizational culture. The absence of interdisciplinary work implies that the work often remains limited within the realm of disciplines such as psychology, education, or computer sciences. To truly grasp the impact of AI on learning effectiveness, it is crucial to address these gaps and consider motivational factors, such as learning orientation, to enhance outcomes. Based on these sights, we propose the following hypotheses.

H5: Learning orientation is positively associated with perceived learning effectiveness.

H6: Learning orientation mediates the relationship between AI usage and perceived learning effectiveness.

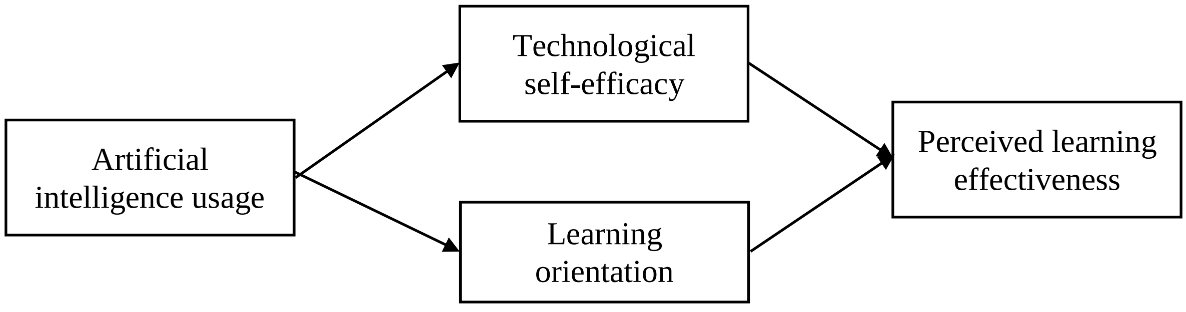

Figure 1: Theoretical model

Methodology

Sampling and procedure

To test the theoretical framework of this study, we surveyed employees working in public, commercial and Islamic banks across Punjab, Pakistan. The target population of the study were employees of commercial banks present in Bahawalpur, Multan, and Lahore, Pakistan. It involves employees from various departments, including operations, customer care, IT, and administration, who are likely to use AI-based tools in their daily work. Furthermore, the choice of such a population is relevant to the research purposes, as bank employees, as can be regularly observed, rely on technology-related systems and must continually adapt to changes in digital systems. For this purpose, the purposive sampling technique was used. This is because these employees were the right candidates to measure AI use, learning outcome, technological self-efficacy and learning orientation. The data in this group were collected using a quantitative approach and structured questionnaires, which provided a broad and diverse representation of employees across various banks. This quantitative study aims to examine how Artificial Intelligence usage influences perceived learning effectiveness by analyzing the mediating effects of technological self-efficacy and learning orientation. This study focuses on the banking industry in Pakistan, where AI usage is gradually dictating the way work is done, how decisions are being made, and how employees are being improved in their daily work.

The sample of the given study is the employees of AI- and IT-related departments of different banks in Bahawalpur, Multan and Lahore. This involves actively engaged in work that utilizes automated systems, applies machine learning, customer analytics, cybersecurity, digital transformation, and data-driven decision-making. It is assumed that employees working with such technologies are the most affected by applying AI, and, thus, can be used to determine the effectiveness of learning with the use of AI in an AI-based workplace. The choice of these types of banks was not random, and the concentration of such diversity was rational since it made it possible to profile the study with as many different experiences associated with AI implementation, technological adoption, and organizational learning culture as possible.

The inclusion criteria for the participants were: (1) the jobholders were currently employed at bank units in Bahawalpur, Multan and Lahore. (2) the jobholders having at least 1 year of job experience in their current organization, and (3) the jobholders must be using AI-enabled systems or technologies either directly or indirectly as a part of their job role. Departments such as IT, operations, customer service, risk management, and finance were selected for their ability to participate effectively, given that customers frequently utilize AI-driven tools.

In this study, cross sectional approach was used, and the study was based on self-report survey method. However, to gauge the adoption and learning of AI, the researcher circulated the questionnaire among employees at various banks. Employees of five commercial banks (MCB limited, Habib bank limited, Alfalah bank limited, Meezan bank limited and UBL), two public banks (National bank and Bank of Punjab) and three Islamic banks (MCB Islamic, Dubai Islamic and Islami bank) were included in this current research. Prior to distributing the surveys, we informed the respondents about the study's purpose and made it clear that their participation was voluntary. We also ensured that their responses would be kept confidential and completely anonymous. Participants provided their informed consent as well. Out data collection journey began with the distribution of questionnaire, which were accompanied by a cover letter that detailed the objective of the study. We opted for a drop-off and collection strategy to distribute 550 questionnaires at several banks. The entire questionnaire was developed in English. We decided to include first line managers as our participants since they offer unique perspective on the day-to-day functions of banks. In the survey, 403 respondents participated. However, 20 of them were removed because they did not meet the criteria. So, we ended up analyzing 348 questionnaires, which resulted in a response rate of 63.2 percent. A survey approach is acceptable with a response rate of 50 percent and above (Baruch & Holtom, 2008). Thus, Table 1 provides an overview of the demographic characteristics of the study sample.

Measurement scales

To measure all constructs in our model, we drew on well-established scales from previous research. We chose the Likert scale because it provides a quantitative way to gauge opinions, perceptions, or attitudes, which are commonly utilized in social sciences to assess subjective experiences. For the current study, the researcher opted for a five-point Likert scale tailored to our study's goal and the specific constructs, with ratings ranging from 1 (strongly disagree) to 5 (strongly agree). However, the AI usage scale with three items was adopted from Liu et al. (2024). Moreover, perceived learning effectiveness with five items was adapted from Hu and Hui (2012). In addition, technological self-efficacy with four items was adapted from Wang and Chuang (2024). Likewise, learning orientation scale with six items was adopted from Wu and Lin (2013). The items of the scales are given in Appendix.

Table 1. Demographics

Particulars	Frequency	(%)	Particulars	Frequency	(%)
Age					
Below 25 years	92	26.7	36-40 years	54	15.5
25-30 years	96	27.5	Above 40 years	30	8.5
31-35 years	76	21.8			
Gender					
Male	231	31.3	Female	117	68.7
Educational Level					
Bachelor's degree	135	38.8	Master's degree	148	42.56
Mphil	40	11.45	Others	25	7.19
Job position					
Customer service officer	81	23.2	Relationship manager	89	25.5
Credit manager	48	13.7	Operations manager	78	22.7
Cash officer	52	14.9			
Job duration					
1-3 years	94	27.01	4-6 years	89	25.7
7-9 years	39	11.2	9-12 years	91	26.3
Above 12 years	34	9.70			

Note: n = 348
Sources: Authors' work SPSS – output

Common Method Bias

Given that the independent and dependent variables data were collected at the same source, we adhered to Kock (2015) recommendations on collinearity to deal with the issue of common method bias (CMB). To assess the data on CMB, two statistical tests were employed. The first researcher conducted Harman's single-factor test, which revealed that the first factor accounted for 41.44% of the total variance, significantly lower than the 50% threshold (Podsakoff et al., 2003). Moreover, we extracted multiple factors with eigenvalues exceeding 1, which shows that a single factor is not dominating the variance. In the current study, to understand collinearity we analyzed it through the variance inflated factor (VIF) and assessed how well we established discriminant validity (Table 2). These results imply that common method variance and multicollinearity do not significantly threaten the validity of our study's findings.

Model Estimation

In the current analysis, the researcher employed structural equation modelling (SEM), a technique that is widely recognized for its ability to extend, develop, or test theories and assess prediction-oriented models (Hair et al., 2021). To estimate SEM, we rely typically on two primary statistical techniques: (1) covariance based SEM known as CB-SEM, (2) variance based SEM, which is often referred to as partial least square structural equation modelling (PLS-SEM). The researcher opted for PLS-SEM for a few key reason: (1) when model is complex, with several contructs and structural paths; (2) when model is relatively new and still developing; (3) when focused on predicting relationships; (4) PLS-SEM does not emphasize overall model fit in the same way as CB-SEM, which means researchers often focus on predictive accuracy rather than strict model fit indices; (5) PLS-SEM helps avoid the limitation of "factor indeterminacy" that can affect CB-SEM (Hair et al., 2021). As a result, we decided to use Smart PLS 4 to test our hypotheses.

Measurement Model

In the PLS-SEM model, there are two critical steps: the measurement (e.g., outer) model and the structural (e.g., inner) model. The outer model outlines how latent construct relate to their indicator, whereas the inner model depicts the connection between predictor and criterion variables (Hair et al., 2021). For the current evaluation, the researcher implemented the PLS algorithm technique along with a weighted scheme for the paths and standardized results to evaluate the outer model's quality. This evaluation helped us assess the reliability and validity of the constructs. To assess the reliability of inter items by analyzing the factor loading, using a threshold of 0.708 as benchmark (Hair et al., 2021). As shown in Table 2 and Figure 2, the factor loading varied between 0.720 and 0.873, which is above the acceptable threshold. The researcher also performed an average variance extracted (AVE) method to evaluate convergent validity yielding values of 0.689, 0.596, 0.607, and 0.699 for variables AIU, LO, PLE, and TSE, respectively, all of which met the required threshold of 0.50 (Hair et al., 2021). Furthermore, we measured the internal consistency and reliability using composite reliability (CR), ensuring that items were prioritized based on their reliability (CR = 0.869, 0.898, 0.885, 0.903) of variables AIU, LO, PLE, and TSE, respectively, as values exceeding 0.70 (Hair et al., 2021).

Table 2 Factor loadings and construct reliability

Construct	Item	Loading	AVE	CR	VIF
AI usage	AIU1	0.836	0.689	0.869	1.575
	AIU2	0.805			1.575
	AIU3	0.848			1.632
Learning orientation	LO1	0.825	0.596	0.898	2.179
	LO2	0.805			1.985
	LO3	0.739			1.720
	LO4	0.772			1.766

	LO5	0.724			1.674
	LO6	0.763			1.895
Perceived learning effectiveness	LE1	0.720	0.607	0.885	1.356
	LE2	0.862			2.639
	LE3	0.724			1.775
	LE4	0.764			1.732
	LE5	0.816			2.484
Technological self-efficacy	TSE1	0.859	0.699	0.903	2.228
	TSE2	0.828			1.903
	TSE3	0.781			1.716
	TSE4	0.873			2.369

Note(s): loading > 0.708; CR > 0.70; AVE > 0.50; VIF < 3.3.
Sources(s): Authors' work PLS-SEM measurement model output

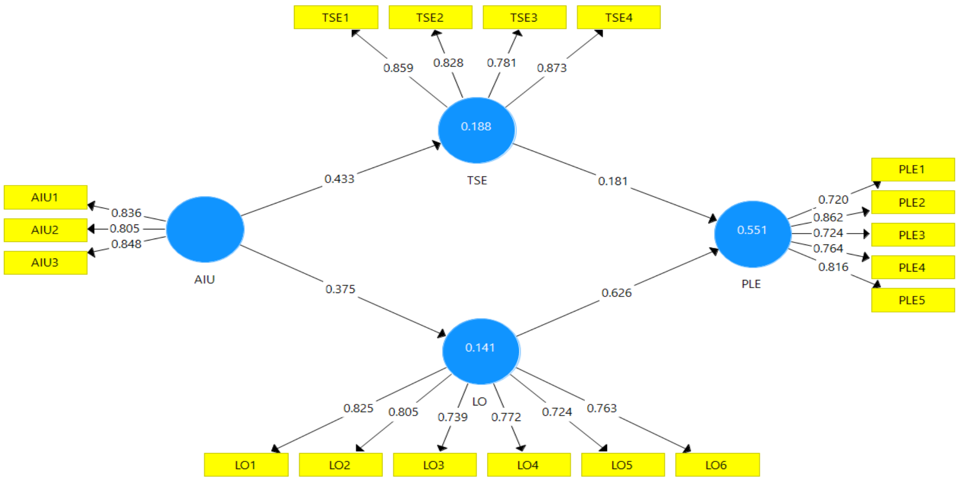

Figure 2. Measurement model

Sources (s): Author's work- Measurement model output

This study explored the discriminant validity of the measurement model using Heterotrait-Monotarit (HTMT) to test its robustness (Henseler et al., 2015). According to Table 3, every HTMT value was under the required threshold of 0.85 (Kline, 2015), which confirms that discriminant validity was achieved. Therefore, the outer model exhibited acceptable reliability along with both convergent and discriminant validity.

Table 3. Discriminant validity (HTMT ratio)

Construct	**AIU**	**LO**	**PLE**	**TSE**
Artificial intelligence usage				
Learning orientation	0.452			
Perceived learning effectiveness	0.388	0.820		
Technological self-efficacy	0.528	0.644	0.621	

Structural model

Once the researcher managed to achieve the requirements of the measurement model, the researcher proceeded to analyze the structural model by determining the significance of path coefficients (e.g., beta value), p-value, t-value, and coefficient of determination (R^2). This was done using a bootstrapping method with 5000 subsample (Henseler et al., 2009), and a two-tailed test at a significance level of 0.05. Figure 3 provides a comprehensive view of the proposed hypotheses within the single model. The results illustrated in Figure 3 display the path coefficient beta values, t-values and the explained variance of the endogenous construct (R^2).

Table 4 deals with the outcomes of the direct paths. The direct and indirect relationships in the model were statistically significant at $p < 0.001$, with t-values exceeding the critical threshold of 1.96, thus confirming the validity of all six hypotheses. For direct paths, AI usage significantly predicted technological self-efficacy ($\beta = 0.433$, $t = 8.387$, $p < 0.001$), supporting hypothesis 1 (H1). This suggests that greater exposure to AI systems enhances employees' confidence in their ability to use technology effectively. In turn, technological self-efficacy had a significant positive impact on perceived learning effectiveness ($\beta = 0.181$, $t = 3.288$, $p < 0.001$), confirming hypothesis 2 (H2). Likewise, AI usage positively influenced learning orientation ($\beta = 0.375$, $t = 6.888$, $p < 0.001$), providing support for hypothesis 4 (H4). Learning orientation had the strongest effect on perceived learning effectiveness ($\beta = 0.626$, $t = 14.073$, $p < 0.001$), supporting hypothesis 5 (H5).

Table 4. Direct paths

Relationships	β Value	SD	t-value	p-value	CI LL/UL	Results
H1: AIU -> TSE	0.433	0.052	8.387	0.000	[0.321/0.525]	supported
H2: TSE-> PLE	0.181	0.055	3.288	0.000	[0.076/0.291]	supported
H3: AIU -> LO	0.375	0.054	6.888	0.000	[0.261/0.475]	supported
H4: LO -> PLE	0.626	0.440	14.073	0.000	[0.531/0.708]	Supported

Note: AIU = Artificial intelligence usage; TSE = technological self-efficacy; PLE = perceived learning effectiveness; LO = learning orientation

Moreover, the indirect effect of AI usage on perceived learning effectiveness through technological self-efficacy was also statistically significant, validating hypothesis 3 (H3) and indicating a meaningful mediation effect. The indirect path from AI usage to perceived learning effectiveness through learning orientation was also significant, confirming hypothesis 6 (H6). The results are shown in Table 5 and Figure 3.

Table 5. Indirect paths

Paths	β Value	SD	t-value	p-value	CI LL/UL	Results
H4: AIU -> TSE -> PLE	0.078	0.025	3.937	0.000	[0.035/0.133]	supported
H5: AIU-> LO -> PLE	0.235	0.035	2.505	0.000	[0.166/0.300]	supported

Note: AIU = Artificial intelligence usage; TSE = technological self-efficacy; PLE = perceived learning effectiveness; LO = learning orientation

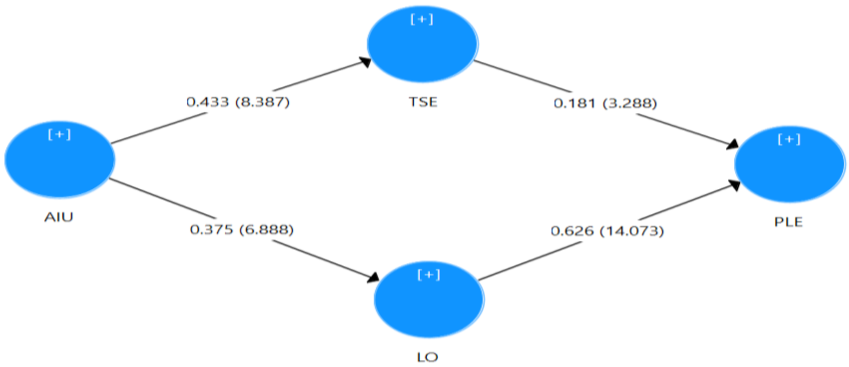

Figure 3. Structural model

Sources (s): Author's work- structural model output

Predictive Relevance and Model Explanatory Power

The model's explanatory power was assessed using the coefficient of determination (R^2), which indicates the proportion of variance in the endogenous constructs explained by the predictor variables. For instance, the R^2 value for technological self-efficacy (TSE) stands at 0.188, which means that 18.8% of the variance in TSE can be attributed to its predictors, mainly AI usage. This points to a moderate level of explanatory power (Schmidt & Bohannon, 1988). On the other hand, the R^2 value for learning orientation (LO) is 0.141, indicating that AIU explain 14.1% of the variance in LO. This suggests a moderate explanatory power, showing that the model effectively captures the factors that influence learning effectiveness. When we look at predictive relevance, the Q^2 value for TSE is 0.122, while for LO, it is 0.077. Since both values exceed the threshold of 0 ($Q^2 > 0$), it shows that the model has a decent predictive relevance for both constructs. Specifically, it can predict outcomes related to TSE and LO and strongly predict those related to PLE. Altogether, these findings affirm that the structural model not only has robust explanatory power but also solid predictive capabilities.

Table 6. Coefficients of determination (R^2) and Predictive relevance (Q^2)

Construct	R- Square	Q-Square
Technological self-efficacy	0.188	0.122
Learning orientation	0.141	0.077
Perceived learning effectiveness	0.551	0.298

Discussion

The results are consistent with the Bandura (1999) social cognitive theory, which majorly states that the exposure to as well as the mastery of the experiences is important in determining the beliefs held by individuals on their ability. This is also supported by recent empirical researches. As an example, Zhao et al. (2022) established that an active use of AI tools positively contributes to the development of a feeling of confidence when using technology systems. In addition, Kim et al. (2020) argued that the adoption of AI technologies in the organization enables its staff members to gain more confidence in their technical abilities in the long term. This finding implies that AI tools do not entail the presence of automatized equipment, as they allow giving the employees a chance to increase their skills and confidence in the possibility. The correlation between self-efficacy and learning outcomes has been thoroughly investigated. Saks et al. (2016) note that self-efficacy is a vital contributor to memory retention, motivation, and all-rounded performance due to its importance as a psychological process.

Moreover, Kuo et al. (2014) found that individuals who feel more confident with technology adapt better to e-learning environments, leading to improved learning results. In the context of this study, it suggests that banking professionals who are more confident in using digital systems are more likely to absorb and apply new knowledge in the workplace. A similar mediation was observed by empirical study conducted by Cheng and Yuen (2018). According to which digital tools initially influenced the feelings of confidence and subsequently the engagement and achievement of learners. The discovery provides a mechanistic interpretation in the historical mammalian reading, suggesting that AI tools become learning advantages through the enhancement of psychological preparedness initially.

Learning orientation deals with the willingness to seek challenges, the acquisition of new information, and feedback among individuals. The implementation of AI systems promotes lifelong learning as it demands evolution and learning new information. Such a result correlates with the theory formulated by Mangels et al. (2006) regarding the growth mindset, and such works as Lee and Chen (2022). According to whom, exposure to AI leads to adaptive learning mindsets among employees. It also assumes the principle of the so-called technology-enabled learning cultures. Therefore, it affirms that AI systems not only present tools but also create an environment that values exploration and up skilling. It is well reinforced by the research (Erez et al., 2013), who emphasized that people focused on learning are more engaging, have superior mnemonic abilities, and are more effective learners. The conclusion supports the psychological aspect of workplace learning, suggesting that attitude is the key parameter rather than the tool. The mediation analysis demonstrated that applying AI leads to an indirect improvement in learning effectiveness through learning orientation. This implies that AI tools address the issue of how motivated and prepared an employee can be to learn, thereby impacting their success in learning. It aligns with Noe et al. (2014), who advocate that learning orientation mediates the relationship between digital exposure and the development outcomes. It is also true that it confirms the results of the research conducted by do Vale Martins et al. (2021), which implies that the organization must allocate funding to AI and combine it with training programs that create favorable learning attitudes in employees.

Theoretical Implications

Grounded in social cognitive theory, this research emphasizes the significant impact of personal cognitive factors, particularly technological self-efficacy and learning orientation, on how employees adjust to and learn in AI-driven environments. SCT claims that learning is a communal activity that depends on the interaction between behaviour, personal and environmental aspects (Bandura, 1986). To take an example, the technological self-efficacy of employees, in the case of banking businesses, would become a determinant of learning aptitude. High self-efficacy employees have a greater chance to actively experiment with AI technologies, request feedback and solve problems effectively, which results in higher learning achievements (Compeau & Higgins, 1995). It is not just using the AI tools that will provide enhanced learning but also depends upon the readiness and confidence level of the individual in using these technology tools. Additionally, the research emphasizes an important factor of learning orientation which is actually an attitude of a person being motivated in developing the skill and competence (Dweck, 1986). SCT suggests that those with a strong learning orientation are more likely to perceive AI-based learning scenarios as opportunities rather than challenges, which enhances their engagement and adaptability (Schunk & Pajares, 2002). This is in line with some initial results that shows how participants' beliefs and motivations represent the primary factors involved in their behavior in technology-enanced learning situation (Zimmerman, 2000). Therefore, the given insights supplement the theoretical framework of SCT in the context of AI-integrated workplace learning, as it suggests that the success of learning such an environment also lies in such psychological characteristics as efficacy and willingness toward the process of learning and developing (Bandura, 2001).

Practical implications

Social cognitive theory points out that self-efficacy, or the belief in our ability to take actions, plays a vital role in how we learn and adapt. In the banking industry, carefully designed AI training programs, like simulation and peer demonstrations, can greatly increase employees' confidence in using technology. For example, research shows that using AI can enhance self-efficacy and increase job satisfaction in team settings. Similarly, studies indicate a strong positive relationship between AI skills and self-efficacy, which in turn benefits creativity and learning performance.

The results indicate that properly designed AI projects in banks can assist in making confident and tech-savvy employees, and these results perfectly match the priorities of SCT about the care of mastery and modeling experiences. According to SCT, there is interaction between behavior, thinking process and the environment which subsequently determines the occurrence of various things like learning and becoming innovative. Studies in organizational context have revealed that self-efficacy is a determining factor in how the use of algorithms in AI influences the changes in innovative behaviour particularly where other attributes such as openness and complexity of job enter the picture. Moreover, the research proves that the positive results of AI on self-efficacy and innovation may be reinforced by a strong learning goal orientation. It means that AI integration can benefit learners more when the learners are motivated. The culture within banking institutions should focus on continuous learning, experimenting and psychological safety to support the realization of the full potential of AI by allowing employees to develop a mindset of viewing AI tools as a source of opportunity instead of being worried that AI tools are threats.

Limitations and Directions for Future Research

Although this study offers some insightful finding, it does have a few limitations worth noting. First, this study heavily relied on self-reported data, which can some time leads to biases, especially regarding self-efficacy and learning orientation. Additionally, since the research is confined to the banking sector, the findings might not apply to other industries that have different levels of tech adoption or learning culture. Cross-sectional design also limits our ability to make a causal connection between AI usage, self-efficacy, and learning outcomes. Further, it does not consider how these relationships might change over time as employees get more familiar with AI tools. In conclusion we should also think about various confounding factors, including the support from the organization, past tech experience, or personal traits.

There are several ways future studies could address these limitations. Firstly, adopting longitudinal research designs would be a great way to dive deeper into the causal and temporary dynamics between AI usage, self-efficacy development and learning effectiveness. Expanding research to cover various industries and cultural contexts could also help us assess the strength and applicability of our current findings. Additionally, looking into how AI usage interacts with psychological or contextual factors like digital resilience, cognitive load, or leadership styles could give us a richer understanding of employee learning behaviors. In the future, studies could really benefit from using experimental or quasi experimental methods to assess the direct effects of AI usage on learning outcomes. Further, qualitative research could provide valuable insights into how employees perceive and experience AI usage and its influence on their motivation and learning in real world settings.

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Appendix

Survey Items	
AI Usage (Liu et al., 2024)	
AIU1	I used artificial intelligence to carry out most of my job functions.
AIU2	I spent most of the time working with artificial intelligence.
AIU3	I worked with artificial intelligence in making major work decisions.
Technological Self-Efficacy (Wang & Chuang, 2024)	
TSE1	When using AI technologies/products, I am not worried that I might press the wrong button and cause risks.
TSE2	When using AI technologies/products I am not worried that I might press the wrong button and damage it.
TSE3	When using AI technology/product, there is nothing that I do not know why.
TSE4	AI technologies/products jargon do not baffle me.
Learning Orientation (Wu & Lin, 2013)	
LO1	We believe that our ability to learn is the key to our competitive advantage.
LO2	Our basic values include learning as the key to improvement.
LO3	Both partners have a well-defined vision in this project.
LO4	We are committed to our partner relationship in this project.

LO5	We place a high value on open-mindedness.
LO6	We encourage our project members to think outside of the box.
Perceived Learning Effectiveness (Hu & Hui, 2012)	
PLE1	My firm provides adequate resources and tools to support my learning of new technologies and systems.
PLE2	My firm gives me opportunities to apply what I learn in real work situations.
PLE3	My firm helps me improve my understanding of how to use new tools and systems effectively.
PLE4	My firm helps me recognize important considerations when working with new technologies.
PLE5	My firm supports my learning of core concepts and skills needed to adapt to technological changes in our operations.