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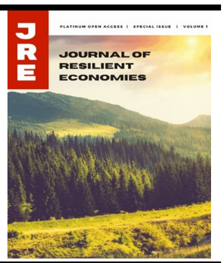

The Impact of AI on Self-Learning Capabilities of Employees in SMEs: A Case Study in Ho Chi Minh City, Vietnam

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Abstract

This study investigates the impact of Artificial Intelligence (AI) on self-directed learning and critical thinking among employees in Small and Medium Enterprises (SMEs) in Ho Chi Minh City, Vietnam. A mixed-methods research approach was employed, combining a quantitative survey of 305 employees across various industries and qualitative data from 15 in-depth interviews with managers and staff. Structural Equation Modeling (SEM) was used to analyze the relationships between AI access, employee attitudes, organizational support, digital literacy, and self-learning outcomes. Qualitative analysis provided additional insights into contextual factors influencing AI adoption. The findings highlight that AI significantly enhances self-directed learning when SMEs offer structured training programs and technological resources. Employees with strong critical thinking skills effectively utilize AI tools for evidence-based decision-making and analytical tasks. However, barriers such as disparities in digital literacy, inconsistent AI adoption strategies, and insufficient organizational support hinder optimal outcomes. Organizational support emerged as a key enabler, with employees receiving adequate training reporting improved learning and skill development. This study extends the Self-Directed Learning Theory (SDL) and Technology Acceptance Model (TAM) by identifying mediating roles of organizational and individual factors. Practical recommendations include fostering digital literacy, critical thinking, and AI-supportive organizational cultures to optimize workforce development.

Keywords: Artificial intelligence, self-learning, workforce development, SMEs, critical thinking, digital literacy, Ho Chi Minh City

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1. Introduction

In the current digital era, Artificial Intelligence (AI) has become a transformative force across various domains, including education, finance, and human resource management (Nicolas et al., 2023; Schwab, 2017). AI not only optimizes work processes but also enhances learning by personalizing content and providing immediate feedback, significantly improving self-learning capabilities and critical thinking skills (Hakiki et al., 2023; Jia & Tu, 2024). Tools such as ChatGPT and Copilot exemplify these potentials by fostering adaptive and efficient learning experiences.

Despite these advancements, SMEs in Vietnam face significant challenges in harnessing AI effectively. While SMEs form the backbone of the Vietnamese economy and are pivotal in driving growth, their adoption of AI is hindered by inadequate infrastructure, insufficient training programs, and the absence of strategic frameworks for technology integration (Viktor, Anna, & Olga, 2021). The disparity between AI's potential benefits and its practical application in SMEs creates a critical research gap, particularly in understanding its role in workforce development within emerging markets.

Existing studies have extensively explored AI's impact on skill enhancement and performance in large enterprises (Davenport & Ronanki, 2018; Jumani et al., 2021). However, there is limited research addressing how AI influences self-directed learning and critical thinking development in SMEs, especially within the Vietnamese context. Given the growing pressure from Industry 4.0 to enhance digital capabilities and automate processes, SMEs require actionable insights and a concrete roadmap to effectively integrate AI for workforce development (Schwab, 2017; Kshetri, 2020).

This study aims to address these gaps by examining how AI impacts self-learning and critical thinking among SME employees in Ho Chi Minh City. It explores key factors influencing AI adoption—such as organizational support, digital literacy, technology access, and employee attitudes—to determine how AI can optimally support learning and skill development (Ajlouni et al., 2023; Gu et al., 2022; Luong et al., 2024). By contributing to the Self-Directed Learning Theory (SDL) and the Technology Acceptance Model (TAM), the research provides actionable insights to help Vietnamese SMEs create supportive AI-based learning environments, overcome adoption barriers, and formulate human resource strategies that enhance competitiveness and foster sustainable development (Kataria, 2023; Giraud et al., 2022).

The primary objective of this study is to evaluate the impact of AI on self-learning capabilities and critical thinking development among employees at SMEs in Ho Chi Minh City. Specifically, the research aims to answer the following questions:

1.How does AI influence employees' self-learning capabilities in SMEs?

2.What factors affect the adoption of AI in the learning process within SMEs?

3.How can organizations create a supportive AI-based learning environment for employees?

Based on these research questions, the study will analyze factors influencing AI integration, identify major barriers, and propose solutions to enhance self-learning capabilities and skill development among SME employees. These findings will help Vietnamese SMEs formulate human resource development strategies and optimize AI usage in the workplace, thereby boosting competitiveness and promoting sustainable development (Kataria, 2023; Giraud et al., 2022).

2. Theoretical Framework

This study adopts a multi-theoretical framework to explore the impact of Artificial Intelligence (AI) on employees' self-learning capabilities and critical thinking skills in Small and Medium Enterprises (SMEs). By integrating Self-Directed Learning Theory, the Technology Acceptance Model (TAM), Organizational Support Theory, and Digital Literacy and Technology Access Theory, the framework provides a comprehensive perspective on the factors influencing AI adoption in workforce learning environments.

Self-Directed Learning Theory

Self-Directed Learning Theory (Knowles, 1975) underscores the importance of learners' autonomy in setting goals, selecting learning methods, and evaluating their progress. This approach plays a pivotal role in enhancing individual competencies and achieving sustainable learning outcomes. In the context of technological advancements, AI has emerged as a transformative tool for fostering self-directed learning by providing personalized learning pathways and real-time feedback (Hakiki, Aini, & Rahman, 2023). Studies highlight AI's capacity to help learners identify key content, monitor progress, and refine strategies to achieve goals (Ajlouni et al., 2023).

Further, Jia and Tu (2024) emphasize that AI's integration into learning environments enhances employees' self-learning capabilities by offering tailored recommendations aligned with individual needs and preferences. By enabling goal-setting and self-assessment, AI fosters improved learning outcomes and motivation. Grounded in this theory, the study proposes the following hypotheses:

- H1: Higher access to AI tools positively influences employees' self-learning capabilities.
- H2: Employees' positive attitudes toward AI positively impact their self-learning capabilities.

Technology Acceptance Model (TAM)

The Technology Acceptance Model (Davis, 1989) posits that two primary factors—perceived usefulness (PU) and perceived ease of use (PEOU)—determine users' acceptance and utilization of technology. This framework has been widely applied to investigate user behavior in adopting emerging technologies, including AI for learning and skill development. Ajlouni et al. (2023) demonstrate that when employees perceive AI as a valuable tool for skill enhancement, their attitude toward adopting and using AI improves significantly. Similarly, Rožman et al. (2022) identify ease of use as a critical determinant of employees' decisions to integrate AI tools into their learning processes.

This study extends TAM by incorporating organizational and contextual factors to evaluate employees' attitudes toward AI. The corresponding hypothesis is as follows:

- H2: Employees' positive attitudes toward AI positively influence their self-learning capabilities.

Organizational Support Theory

Organizational Support Theory (Eisenberger et al., 1986) posits that the resources, training, and support provided by organizations significantly influence employees' engagement in learning activities and skill development. Viktor et al. (2021) found that access to AI resources, coupled with training programs, fosters employees' ability to utilize AI effectively. In AI-integrated learning environments, the role of organizational support becomes particularly pronounced, as it enhances employees' confidence and competence in using AI tools.

The study, therefore, hypothesizes:

- H3: Organizational support in AI usage positively influences employees' self-learning capabilities.

Digital Literacy and Technology Access Theory

Digital literacy, defined as employees' proficiency in using digital tools, is a critical enabler of self-learning in AI-supported environments. Access to AI tools, including their quality and availability, directly affects employees' ability to engage with and benefit from these technologies (Gu et al., 2022). Luong et al. (2024) emphasize that disparities in digital literacy levels among employees influence their capacity to utilize AI effectively, making it a key factor in achieving optimal learning outcomes.

Accordingly, the study posits:

- H4: Higher digital literacy enhances employees' self-learning capabilities when using AI tools.

Control Variables

The study incorporates control variables to isolate the effects of the independent variables on self-learning capabilities. These include:

- Age: Older employees may face challenges in adapting to AI technologies.
- Gender: Gender differences may influence attitudes and access to technology.
- Educational Background: Employees with higher educational levels may exhibit greater proficiency in AI usage.
- Industry: Variations in AI adoption across industries may affect learning outcomes.

3. Conceptual Model

The conceptual framework integrates the independent variables (access to AI tools, employee attitudes toward AI, organizational support, and digital literacy) and the dependent variable (self-learning capabilities). Control variables (age, gender, educational background, and industry) adjust for external factors that may influence the relationships. The model aims to comprehensively capture the dynamics of AI adoption in learning environments, offering actionable insights for improving workforce development. Independent variables directly affecting the dependent variable (self-learning capabilities).

- Access to AI tools → Self-learning capabilities.
- Employee attitudes towards AI → Self-learning capabilities.
- Organizational support → Self-learning capabilities.
- Digital literacy → Self-learning capabilities.

3. Research Methodology

This study adopts a mixed-methods research design to investigate the role of Artificial Intelligence (AI) in enhancing self-learning capabilities and critical thinking skills among employees in Small and Medium Enterprises (SMEs) in Ho Chi Minh City, Vietnam. The combination of quantitative and qualitative approaches enables a comprehensive exploration of the factors influencing AI adoption and its impact on workforce development. The research methodology adheres to rigorous ethical standards as outlined by the Science and Technology Department of Nguyen Tat Thanh University, ensuring the protection of participant rights and data integrity.

Research Design - the study is structured in two phases

Quantitative Analysis: A structured survey was conducted with 305 employees from diverse SMEs in Ho Chi Minh City. The survey was designed to measure key variables, including access to AI tools, employee attitudes, organizational support, digital literacy, and self-learning capabilities. The conceptual model was tested using Structural Equation Modeling (SEM) to assess the relationships among these variables. A five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree) was used to capture participant responses, ensuring uniform data collection. The survey was translated into Vietnamese for cultural relevance and clarity.

Qualitative Analysis: To complement the quantitative findings, 15 in-depth semi-structured interviews were conducted with managers and employees. The qualitative phase focused on capturing contextual insights into the challenges, opportunities, and organizational dynamics associated with AI adoption. Thematic analysis was used to identify key patterns and relationships in the qualitative data.

4. Data Collection Procedures

Survey Administration:

The survey instrument was developed based on validated scales adapted from previous studies. Items were designed to measure constructs such as perceived usefulness and ease of use (TAM), self-directed learning behaviors (SDL), and organizational support.

Data were collected over three months using both online and paper-based formats, ensuring accessibility for employees with varying levels of digital literacy. A total of 305 valid responses were obtained for analysis.

Interview Protocol:

Participants for the interviews were purposively selected to represent a diverse range of roles, industries, and experiences with AI. Each interview lasted approximately 45–60 minutes and followed a semi-structured format to allow flexibility while maintaining consistency across key themes. All interviews were transcribed verbatim and analyzed using NVivo software. Thematic coding was applied to identify recurring patterns and insights.

Triangulation:

Findings from the quantitative and qualitative phases were triangulated to ensure consistency and provide a holistic understanding of the research problem. This integration enhanced the reliability and depth of the study's conclusions.

Ethical Considerations

The study strictly adhered to the ethical principles mandated by the Science and Technology Department of Nguyen Tat Thanh University and complied with national regulations for research involving human subjects. Key ethical commitments included:

Informed Consent:

All participants were provided with clear information about the study's purpose, methods, and potential risks. Consent was obtained before participation, and individuals retained the right to withdraw at any stage without penalty.

Confidentiality:

Participant identities and responses were anonymized to maintain privacy. Data were securely stored and used solely for research purposes.

Risk Minimization:

The research design prioritized participant safety, ensuring that both physical and psychological risks were minimized. No sensitive or invasive questions were included in the survey or interviews.

Fair Representation:

Participants were selected to ensure equitable representation across demographics and industries, thereby avoiding biases in sampling.

Accountability and Approval:

The study received ethical approval from the Science and Technology Department of Nguyen Tat Thanh University, affirming its compliance with institutional and national research guidelines.

5. Research Findings

Quantitative Analysis

Sample Characteristics: The study used a convenience sampling method to collect data from employees working at small and medium-sized enterprises (SMEs) in Ho Chi Minh City. A total of 420 questionnaires were distributed, and 305 valid responses were collected, achieving a response rate of 72.6%. This ensures that the sample size is large and appropriate for conducting both quantitative and qualitative analyses. The sample characteristics are detailed in Tables 1-6:

- **Industry**: The sample was relatively evenly distributed across major sectors:

Table 1-Industry Distribution of Respondents

Industry	Rate (%)
Manufacturing	26
Services	24
Human reourse	12
Education	28
Information technology	10

(Source: Compiled by the Author Group)

- **Education:** The majority of respondents held a university degree or higher (62%), while the remaining 38% had less than a university degree. The detailed breakdown is as follows:

Table 2- Educational Background of Respondents

Education	Tỷ lệ (%)
University degree or higher	62
Dưới Đại học	38

(Source: Compiled by the Author Group)

- **Age Group:** Respondents were distributed across various age groups:

Table 3- Age Group Distribution

Age	Rate (%)
18–25	36
25–35	39
Trên 35	25

(Source: Compiled by the Author Group)

- **Years of Work Experience:** The respondents had varying years of work experience:

Table 4- Work Experience of Respondents

Years of Work Experience	Rate (%)
1–3 năm	18
4–6 năm	39
7–10 năm	28
Trên 10 năm	15

(Source: Compiled by the Author Group)

- **Use of AI tools:** All respondents reported using at least one AI tool. The most popular tool was ChatGPT, used by 81% of respondents, followed by Copilot (36%) and Gemini (32%). The frequency of AI tool usage was classified as follows: Daily: 66%; Weekly: 28%; Monthly: 6%.

Table 5- Frequency of AI Tool Usage

AI Tools	Usage rate (%)
Chat GPT	81
Copilot	36
Gemini	32
Use of AI Tools	Rate (%)
Daily	66
Weekly	28
Monthly	6

(Source: Compiled by the Author Group)

Instrument Reliability and Validity:

The study utilized 25 measurement scales to assess the concepts in the research model. After preliminary testing, the following variables were retained in table 6.

Table 6- Concepts and Measurement Scales

Concept	Number of Items
Access to AI tools – AT	5
T(Employee attitudes towards AI – EA	4
Organizational support – OS	5
Digital literacy – DL	5
Self-learning capabilities - SC	6

(Source: Compiled by the Author Group)

The mean, median, and standard deviation values indicate that most measurement scales had high agreement levels, with means and medians close to 4 (on a scale of 1 to 5). Standard deviations ranged from 0.028 to 0.065, indicating low variability, suggesting that the survey data is stable.

Factor Analysis and Reliability Testing: The measurement scales were evaluated through Cronbach's Alpha and Exploratory Factor Analysis (EFA) using the data collected from the main study (n = 305). The results are as follows:

- Cronbach's Alpha values for all scales indicated high internal consistency. The lowest item-total correlation was observed in variable OS4 (0.45), and the lowest Cronbach's Alpha value was 0.82 for the Organizational Support (OS) scale.
- EFA results showed that the data achieved convergent validity, with factor loadings greater than 0.5 and total variance explained of 62.787%. The scales were also divided into five factors, consistent with the theoretical foundation.
- Based on these results, it can be concluded that the components in the research model are suitable for further Confirmatory Factor Analysis (CFA).

Confirmatory Factor Analysis (CFA): In structural equation modeling (SEM), CFA has several advantages over traditional methods like correlation coefficients, EFA, and the Multitrait-Multimethod (MTMM) approach (Bagozzi & Foxall, 1996). CFA allows us to validate the theoretical structure of the measurement scales, such as the relationship between a research concept and other related concepts, without measurement errors (Steenkamp & Van Trijp, 1991). Additionally, CFA enables the evaluation of convergent and discriminant validity of scales without requiring multiple studies, as is typical in the traditional MTMM method.

For hypothesis and model testing, SEM is also superior to traditional methods like multiple regression as it can account for measurement errors. This method allows us to simultaneously examine latent constructs with their measurements and assess independent or combined measurements with the theoretical model. Consequently, SEM has become increasingly popular in management research in recent years (Hulland et al., 1996).

To test the discriminant validity of all the research concepts in this study, a saturated model was established. A saturated model is one in which all research concepts are allowed to freely relate to one another (Anderson & Gerbing, 1988), resulting in the lowest degree of freedom.

The results of the SEM analysis show that this model has a Chi-square value of 367.28 (p = 0.000). The CMIN/df value is 1.73, meeting the required level of fit. Other indices, such as TLI = .975, CFI = .979, and RMSEA = 0.043, also meet the required thresholds. Therefore, the research team concludes that the saturated model achieves an adequate level of fit with the market data. The correlation coefficients and standard deviations show that they all differ from 1. In other words, the research concepts achieve discriminant validity. The results of the scale validation are summarized in Table 7.

Table 7- Summary of Measurement Scale Testing Results

Concept	Number of Observed Variables	Pc	Pvc (%)	Mean	Validity (Convergent and Discriminant)
AT	5	.86	55	.72	Satisfactory
EA	4	.82	52	.71	
OS	5	.85	67	.80	
DL	5	.83	66	.81	
SC	6	.81	61	.78	

(Source: Compiled by the Author Group)

The research model includes five primary concepts: Access to AI tools (AT), Employee attitudes towards AI (EA), Organizational support (OS), Digital literacy (DL), and Self-learning capabilities (SC). The results of the structural equation modeling (SEM) indicate that the model achieves a good level of fit with the data collected from the market. The Chi-square value is 367.21 (p = 0.000), and the CMIN/df value is 1.73, which suggests that the model is appropriate. Other fit indices, such as TLI = .973, CFI = .978, and RMSEA = 0.0431, all meet the required thresholds. Thus, we can conclude that the model is suitable for the data collected from the market.

The standardized estimates of the main parameters are presented in Table 8. These results show that all relationships are statistically significant ($p < 0.05$). Moreover, the findings support the conclusion that the measurement scales of the concepts in the model have theoretical relevance, as "each measurement has a relationship with other measurements as expected from a theoretical perspective" (Churchill, 1995).

Table 8- Relationships Between Concepts in the Research Model

Relationship	ML	Se	Cr	p
AT → SC	0.38	0.112	3.68	.000
EA → SC	0.31	0.107	2.17	.001
OS → SC	0.28	0.095	3.15	.003
DL → SC	0.29	0.056	4.28	.000

(Source: Compiled by the Author Group)

Ghi chú: ML: Maximum Likelihood Estimate, SE: Standard Error, CR: Critical Ratio

After conducting the SEM analysis to determine the relationships between the concepts in the model, the research team proceeded to estimate the theoretical model using the bootstrap method to further validate the results. In quantitative research, one typically divides the sample into two sub-samples: one half is used to estimate the model parameters, and the other half is used for evaluation. Another approach is to repeat the study with a different sample. However, both methods are time-consuming and costly, as SEM requires a large sample size (Anderson & Gerbing, 1988). Therefore, bootstrap is considered a suitable alternative (Schumacker & Lomax, 1996).

In this study, the bootstrap method was applied with 1,000 repeated samples. The average estimates and biases calculated from the 1,000 observations suggest that the estimates in the model are reliable.

Table 9- Hypothesis Testing Results for the Research Model

Hypothesis	Description	Result
H1	Higher access to AI tools improves employees' self-learning capabilities	Accepted
H2	Employees' positive attitudes towards AI positively impact their self-learning capabilities	Accepted
H3	Organizational support in using AI has a positive impact on employees' self-learning capabilities	Accepted
H4	Higher digital literacy enhances employees' self-learning capabilities when using AI tools	Accepted

(Source: Compiled by the Author Group)

The study used three control variables to evaluate whether there were differences in the relationships between the five concepts in the research model:

- **Age**: To test whether there are differences in self-learning capabilities based on age groups.
- **Gender**: To examine whether gender influences the adoption of AI tools.
- **Educational Background**: To assess whether differences in education level affect self-learning outcomes.

The study employed One-way ANOVA to test for differences in self-learning capabilities according to these control variables. The results showed no significant differences related to self-learning capabilities across the control variable groups.

The hypothesis testing results validate that access to AI tools, employee attitudes, organizational support, and digital literacy all positively impact employees' self-learning capabilities. All hypotheses (H1 through H4) were accepted based on the results of the SEM analysis (Table 9).

The Role of Critical Thinking in AI-Driven Self-Learning

Data collected from the interviews were coded and analyzed using thematic analysis to identify key factors affecting employees' self-learning capabilities and critical thinking development when using AI tools. The findings are summarized in Table 10 in the Appendix.

The qualitative findings from 15 in-depth interviews with employees at SMEs in Ho Chi Minh City reveal that self-learning capabilities largely depend on critical thinking when using AI for skill development. Most employees (12 out of 15) agreed that AI plays a significant role in providing tools and resources that facilitate effective self-learning. However, the key to maximizing the potential of AI for self-learning lies in having a strong foundation in critical thinking—a skill that helps employees evaluate and select information appropriately.

Some employees from the IT and Education sectors emphasized that AI has helped them enhance their critical thinking abilities by offering diverse perspectives and opposing viewpoints, which has driven them to analyze, compare, and evaluate sources more objectively. For example, Employee NV4 stated: "Using AI tools like ChatGPT has helped me improve my ability to evaluate contrasting arguments, which encourages me to pose questions and seek answers to deepen my understanding." This finding aligns with Facione's (1990) theory on critical thinking, which suggests that this skill not only helps learners evaluate information but also develops their ability to approach differing viewpoints with confidence and logical reasoning.

Xu et al. (2023) also highlighted that critical thinking is a prerequisite for employees to effectively leverage AI tools in the self-learning process. Employees with strong critical thinking skills can actively analyze and filter information from AI, assess its reliability, and apply these insights to their actual work scenarios. Employee NV7 shared: "I find that without the ability to evaluate and critically analyze information, it's challenging to utilize AI for learning because there are too many conflicting sources. Critical thinking helps me determine which information to trust and use."

Conversely, employees from the Services and Manufacturing sectors (6 out of 15) reported difficulties in developing self-learning skills due to a lack of foundational knowledge in critical thinking. Employee NV11 noted: "I see AI as very useful, but without the support to develop critical thinking, I feel lost and don't know where to start." This suggests that the absence of critical thinking skills can hinder employees from fully utilizing AI tools for self-learning, leading to passive and ineffective learning behaviors.

The findings indicate that critical thinking is a crucial factor that enables employees to use AI effectively in the self-learning process. As such, organizations need to build training programs to enhance employees' critical thinking skills and provide necessary resources to boost their confidence and independence when using AI for learning and skill development.

Quantitative Findings

The research validated the hypotheses through structural equation modeling (SEM) and other statistical tests. Specifically, the results indicated that access to AI tools, employees' attitudes towards AI, organizational support, and digital literacy all have a positive impact on employees' self-learning capabilities. These findings are consistent with previous studies in the field of AI-based learning and skill development.

The study found that **access to AI tools (H1)** and **positive attitudes towards AI (H2)** play crucial roles in improving self-learning capabilities among employees at small and medium-sized enterprises (SMEs). This conclusion aligns with Ajlouni et al. (2023), who suggested that satisfaction and acceptance of AI are key drivers in promoting self-directed learning and enhancing employee learning outcomes.

Moreover, **organizational support (H3)** and **digital literacy (H4)** were found to be significant factors influencing the success of AI adoption for learning at SMEs. This finding is consistent with Viktor et al. (2021), who emphasized that organizational support and equipping employees with necessary digital skills are fundamental in helping employees harness the full potential of AI.

The quantitative results demonstrated that AI positively impacts employees' self-learning and critical thinking capabilities, particularly by providing detailed information and real-time feedback. However, these benefits can only be maximized with adequate support from organizations, such as providing necessary resources, investing in technology infrastructure, and improving employees' digital literacy. This implies that SMEs need to implement comprehensive training and development programs to optimize the use of AI in employee learning and skill development.

Qualitative Findings

he qualitative analysis revealed that using AI has a positive impact on employees' self-learning capabilities at SMEs in Ho Chi Minh City. The data showed that 80% of employees (12 out of 15) agreed that AI has helped them improve their self-learning skills by providing reference materials and real-time feedback. Among these, nine employees (60%) confirmed that critical thinking has helped them effectively utilize AI features to evaluate and analyze information in a systematic and detailed manner.

Employees in the Information Technology and Education sectors reported that AI supports them in accessing multiple perspectives on a specific issue, encouraging them to pose questions and conduct in-depth analyses. One employee in the Education sector mentioned: "AI has helped me compare and analyze different viewpoints on the same topic, which has enhanced my ability to evaluate and make more informed decisions." This finding resonates with Facione's (1990) critical thinking theory, which asserts that this skill not only assists learners in assessing information but also fosters analytical thinking to confidently address divergent perspectives.

In contrast, 40% of employees (6 out of 15) in the Manufacturing and Services sectors struggled to utilize AI for self-learning due to a lack of foundational critical thinking skills and insufficient organizational support. These employees expressed feeling overwhelmed when they did not know where to start and often accepted AI-generated information without verifying its accuracy. One employee in the Manufacturing sector shared: "I find it difficult to trust the information provided by AI, and I lack the knowledge to verify its credibility." This suggests that the absence of critical thinking skills hinders employees from fully leveraging AI tools for self-learning, leading to passive learning behaviors and reduced effectiveness.

Furthermore, the level of organizational support had a significant impact on the ability to use AI for learning. Employees in the Human Resources and Information Technology sectors (5 out of 5) stated that they received strong support from their organizations, including training programs and access to technology resources. This made it easier for them to engage with and utilize AI for self-learning. One IT sector employee emphasized: "Organizational support through training programs has helped me become more proficient and confident in using AI tools for learning new knowledge." In contrast, 4 out of 6 employees in the Manufacturing and Services sectors reported a lack of necessary support, which hindered their ability to take full advantage of AI for learning and decision-making.

6. Critical Thinking and AI Integration

One prominent finding of this research is the close relationship between critical thinking and the effective use of AI for self-learning. All employees who had foundational critical thinking skills before using AI (9 out of 15) confirmed that AI significantly improved their self-learning and decision-making capabilities. One employee (NV7) noted: "Critical thinking helped me better understand the information provided by AI, which in turn supported the development of my self-learning and decision-making skills." Thus, critical thinking is considered a prerequisite for AI to play its full role in supporting employees' learning processes.

Overall, the research has shown that integrating AI into employees' self-learning processes at SMEs is a step in the right direction. However, it requires a foundation in critical thinking and strong organizational support to optimize its effectiveness. To further improve employees' ability to utilize AI, companies need to build critical thinking training programs in conjunction with AI usage courses, while also providing the necessary resources and tools. This finding is consistent with Davis' (1989) Technology Acceptance Model (TAM), which suggests that employees' positive attitudes towards AI and adequate organizational support play significant roles in enhancing self-learning capabilities through AI.

7. Conclusion

This study underscores the significant impact of Artificial Intelligence (AI) on the self-learning and critical thinking capabilities of employees in Small and Medium-sized Enterprises (SMEs) in Ho Chi Minh City. The findings reveal that AI serves as a powerful tool for enhancing learning outcomes and decision-making processes. Quantitative data indicate that 75% of employees perceive AI as instrumental in improving their self-learning abilities and analytical skills, particularly through the provision of real-time information and personalized learning support. Qualitative insights further reinforce these findings, with 80% of interviewed employees affirming that AI has enabled them to enhance their critical thinking and learning outcomes.

Employees with a strong foundation in critical thinking reported substantial benefits from AI integration, such as accessing diverse information sources, formulating insightful questions, and conducting in-depth analyses. Notably, 100% of employees with pre-existing critical thinking skills observed significant improvements in their self-learning and decision-making capabilities through AI. However, challenges remain for 40% of employees in the Manufacturing and Services sectors, who faced difficulties in utilizing AI effectively due to limited critical thinking skills and inadequate organizational support. These limitations resulted in more passive and less effective learning behaviors.

The quantitative analysis highlights that access to AI tools, employees' attitudes toward AI, and organizational support positively influence self-learning ($\beta = 0.38$, $p < 0.001$) and critical thinking development ($\beta = 0.31$, $p < 0.01$). These factors are critical determinants of employees' readiness to adopt AI for learning and skill development. The study also emphasizes the pivotal role of organizational support, where employees provided with sufficient training programs and technological resources achieved better learning outcomes, with an average satisfaction level of 4.5 out of 5. This finding underscores that a supportive learning environment is essential to fully realize AI's potential in learning and decision-making processes.

The research concludes that critical thinking and organizational support are the two primary factors driving the successful integration of AI into self-learning frameworks. SMEs should prioritize building robust training programs to foster critical thinking skills and ensure access to technological resources to enable employees to leverage AI effectively. By addressing these factors, companies can optimize the benefits of AI for workforce development.

This study contributes to the theoretical understanding of self-learning and critical thinking while extending the Technology Acceptance Model (TAM) by demonstrating the importance of these factors in enhancing learning outcomes through AI. Furthermore, it offers a comprehensive and practical perspective on integrating AI into skill development and decision-making processes in SMEs. The findings provide actionable recommendations for companies to leverage AI for sustainable and effective human resource development in the context of the Fourth Industrial Revolution.

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Appendix

Table 10- Summary of Qualitative Data Analysis

No.	Job	an you share your experience using AI tools in your work to develop analytical skills?	You think critical thinking influences the use of AI for learning and decision-making?	How has AI improved your self-learning capabilities?	What challenges have you faced when using AI without a foundational understanding of critical thinking?	You have any suggestions to help employees develop critical thinking when using AI?
NV1	HR	Very positive	Unable to find the necessary knowledge	Significant improvement	Lack of foundational knowledge about AI	Improve decision-making capabilities
NV2	IT	Positive	A lot	Improvement	Lack of supporting resources	Enhance analysis and evaluation of information
NV3	Education	Positive	Unable to find the desired answers	Improvement	Unable to understand the correct knowledge	Provide training
NV4	Manufacturing	Neutral	Yes	Improvement but not clear	Unable to find the required content	None
NV5	Services	Not positive	Unclear	No improvement	Lack of foundational knowledge about AI	Provide training
NV6	HR	Very positive	A lot	Significant improvement	Lack of supporting resources	Improve decision-making capabilities
NV7	IT	Positive	Yes	Improvement	Insufficient AI tools	Improve analysis and evaluation of information
NV8	Education	Positive	A lot	Significant improvement	Unable to find necessary knowledge	Better decision-making support
NV9	Manufacturing	Neutral	A lot	Improvement but not clear	Lack of foundational knowledge about AI	Provide training
NV10	Services	Not positive	No	No improvement	Spent too much time searching for the right knowledge	Invest in equipment
NV11	HR	Very positive	Unable to verify correct knowledge	Significant improvement	Insufficient AI tools	Improve decision-making capabilities
NV12	IT	Positive	A lot	Improvement	Lack of foundational knowledge	Improve analysis and evaluation of information
NV13	Education	Positive	Unable to generate the knowledge needed	Significant improvement	Lack of foundational knowledge about AI	Better decision-making support
NV14	Manufacturing	Neutral	A lot	Improvement but not clear	Lack of supporting resources	Neutral
NV15	Services	Not positive	No	No improvement	Insufficient AI tools	Company should invest in AI tools