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AI Literacy and Skills for Organizational Transformation in Thai Enterprises

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Abstract

Purpose: This study aims to investigate the current state of AI literacy, identify critical skill gaps, and evaluate the effectiveness of training strategies for driving successful AI-driven organizational transformation within Thai enterprises. **Design/Methodology/Approach:** A mixed-methods approach was employed, beginning with a quantitative survey of 294 professionals to gauge baseline AI awareness and confidence. This was followed by in-depth qualitative interviews with three key stakeholder groups: employees (n = 12), trainers (n = 6), and HR professionals (n = 3) from various. **Findings:** The research reveals a strong motivation for AI upskilling but a significant generational and role-specific skill gap, particularly in practical application and ethical understanding. Training initiatives focused on tools like ChatGPT demonstrably improve efficiency, save time, and foster positive employee attitudes. However, major challenges persist, including unequal access to technology, varying proficiency levels, and a need for more user-friendly AI design for diverse demographics. **Practical Implications:** The organizations need to come up with ongoing and role specific trainings, use internal champions as instructors and combine AI learning with re-engineering of processes. Accessibility through the provision of the required tools is important. A way that policymakers can contribute is by promoting initiatives that can introduce AI education and resources to more people. **Originality/Value:** This study provides a nuanced, multi-stakeholder perspective on AI adoption in Thailand, moving beyond technical implementation to focus on the human and organizational factors critical for transformation. It offers unique cultural insights, such as the emphasis on user-friendliness for older generations, which are absent in broader global studies.

Keywords

Artificial Intelligence, AI Literacy, Organizational Transformation, Skills Development, Human Resource Management, Thailand, Qualitative Research,

Training & Development

1. Introduction

This technological revolution has brought both new opportunities as well as challenges that have never been experienced by organizations globally. Specifically, in the new economy of Thailand, where the government's Thais 4.0 initiative, as well as the Digital Economy Promotion Agency, are already fueling digital transformation, the adoption of AI technologies has now become a strategic necessity (Sararuch et al., 2025). However, despite these efforts, surveys conducted in the industry have shown that only 20 - 30 percent of Thai professionals claim to be highly AI proficient, which suggests a critical lack of workforce preparedness that can potentially become an obstacle to the digital transformation agenda of the country.

This is not just a technical implementation issue but also a human capital development issue. Despite the increasing availability of AI technologies, the human factor frequently becomes an obstacle to change within any organization, particularly the skill and literacy deficit. Visuthiphol and Pankham (2025) argue that organizations in the emerging economies continue to experience skills related challenges in the process of adopting new technologies. Their study highlights that insufficiency of digital preparedness by the staff significantly extends change efforts. In addition, they claim that it is important to alleviate these human-capital constraints to make the introduction of artificial intelligence for successful and sustainable implementation possible. The detachment is specifically very high in the emerging economies that have fallen prey to the digital divide and where the study has been biased, in the Western or technology-based industries, with an overall knowledge gap about the Thai setting (Muankaew & Levermore, 2025). AI literacy, as a non-technical concept of cognitive insight, practical use, and ethical comprehension, has become a pivotal facilitator of effective change, enhanced decision-making skills, operational effectiveness, and the ability to innovate within organizations.

This paper fills this research gap by looking into AI literacy in terms of various stakeholder views in the different Thai sectors, such as the manufacturing sector, information technology sector, and corporate sector (Ueasangkomsate, 2025). The given study provides an in-depth insight into the human aspect of AI assimilation through the interrogation of existing levels of digital literacy, the evaluation of the training programmes, and the assessment of skill deficiencies as well as the implementation issues. The results can be exploited by organisations that strive to address the challenges of digital transformation and enhance the general theoretical knowledge of technology adoption in emerging markets.

2. Theoretical Background

2.1. Conceptualizing AI Literacy

Artificial intelligence (AI) literacy requires more than simple technical expertise;

it requires a complex knowledge of the complex field of AI. Jewapatarakul and Ueasangkomsate (2024) assume that there are three fundamental components of AI literacy namely cognitive knowledge, practical aptitude, and social consciousness. This includes a base level of knowledge of machine learning, natural language processing and neural network structures, along with a certain level of procedural skill in the use of tools such as ChatGPT and Midjourney. In addition, AI literacy development is also promoted by the development of critical thinking which can put the implications of AI use in data privacy, targeted interventions, and societal influence into context (Kraiwanit & Terdpaopong, 2024). With the dynamic nature of AI application into organizational processes, the cultivation of such literacy becomes a key identifying determinant to employees so that they can act responsibly and effectively to apply AI technologies in their practice.

2.2. AI's Role in Organizational Transformation

The digital era and AI's ability to improve efficiency, innovation, and decision-making are having a significant impact on organizational change. Theoretical frameworks in the light of which factors that predetermine the adoption of AI can be made sense of are the Technology Acceptance Model (Le et al., 2024) and Diffusion of Innovations (Rogers, 2003). Research across the world is pointing to the transformative capability of AI; McKinsey studies show that as many as 40 percent of workflow processes can be entirely automated by AI, which can drastically increase productivity. In many cases, though, in developing markets like Thailand, it is the infrastructure limit that hampers adoption, and resource limits, which is why context-specific strategies are so critical.

2.3. Skill Gaps in AI Adoption

The widespread talent shortage in all industries is one of the challenges facing AI-led transformation. According to the World Economic Forum Future of Jobs report, Depoo et al. (2025), practicing AI skills is not available in the non-technical segments. The manufacturing industry does not have predictive maintenance and AI-based diagnostic mechanisms, and service industries are not yet plagued by real-time engineering and content creation of the generative AI platform. Another important gap is ethical (bias mitigation and data governance). All these weaknesses prove the point that there needs to be certain training programs that would not only discuss the technical side of the AI implementation but also the ethical one. Proper AI training methodologies emphasize experiential learning. Leal et al. (2025) support workshops, simulations, and ongoing cycles of learning that help employees to engage with AI tools in practice. HR can have a significant role as a change agent that instills a culture of AI acceptance and helps overcome resistance, in particular, in older demographic or less digitally fluent employees. The keys to success are empowering internal champions, tailoring the content to the role, and committing to AI training for the overall objectives of the organization. Additionally, the HR needs to work with the leadership to ensure that the AI project is strategically aligned with the objectives so that the training can be translated into measurable organizational value.

2.4. Thai Context and Research Gaps

The AI National Strategy (2018-2027) of Thailand seeks to make the country an AI hub in the region, but issues related to the urban-rural digital divide and unequal access to technology remain. Although local research has already started to consider the application of AI, there is still a lack of qualitative studies investigating the experiences of stakeholders, especially employees, trainers, and HR professionals. The gap in this paper will be addressed by discussing the human side of the AI transformation and will include data on the cultural, generational, and organisational factors in Thailand that affect AI literacy and adoption (Dittmar, 2025). This way, it can help to understand how AI can be leveraged successfully in developing economies.

3. Methodology

3.1. Research Design

The present study adopted a qualitative-dominant mixed-method research design to thoroughly examine AI literacy and skills development in Thai enterprises. A qualitative interview (intensive) and a quantitative survey (mixture) were chosen as tools to provide breadth to the general trends and depth to the knowledge of subtle experience (Pandit et al., 2025). The quantitative measure provided objective information on the measures of AI literacy, confidence, and perceived gaps in skills in a representative sample of professionals. The qualitative strand, which was the focal point of this study, employed semi-structured interviews to elicit rich and detailed accounts of key stakeholders in the adoption and training of AI. The analysis and description of the qualitative data were accomplished with reference to the thematic analysis as the primary methodological framework. However, to discover the patterns, challenges, and strategic implications that might be capitalized upon when transforming the organization (Promma et al., 2025). Such a design suited the study of complex human and organizational phenomena especially well, in which contextual knowledge plays a central role.

3.2. Data Collection

These two significant sources of data were an extensive online survey and semi-structured in-depth interviews (Alhusban et al., 2025). The survey sample comprised 294 professionals working in different areas in Thailand, such as information technology (30 percent), manufacturing (40 percent and corporate services 30 percent). Included in the instrument were structured questions designed to approximate the degree of basic AI knowledge (e.g., How confident are you in your knowledge of the basic AI concepts?), attitudes toward AI tools (How confident are you that you use AI technologies in your daily working?), skill gaps (In which areas do you believe you are least prepared to use AI?), and perceptions about AI and its impact on productivity and career growth. The qualitative data consisted of 21 semi-structured interviews that were held with three different stakeholder groups. Group 1 (Employees, n = 12) comprised of participants like Nithi Intawarat, a lawyer who uses AI to write e-mails and check the grammar, and Khun Than, a graphic designer who relies on AI to generate creative ideas and save some time using such tools as Midjourney and ChatGPT. Group 2 (Trainers, n = 6) comprised the following professionals: Mr. Trin, a freelance consultant and with the practice based on increasing productivity through the application of AI tools such as ChatGPT and Canva, and with the orientation based on the application-related instructional approaches. Group 3 (HR Professionals, n = 3) included senior professionals (e.g., Ms. Ratsanee Sapetch, human resources manager) with over 20 years of work experience and designed courses on training on ChatGPT to be provided to the staff of the management tier and estimated the actions to implement to bridge the competence gap (Ghosh, 2025). All the interviews were recorded and summarized with the NotebookLM to extract key themes and findings. Organizational training records were used to triangulate and validate interview findings with supplementary data in the form of HR reports.

The questionnaire was structured to address AI literacy per se, using questions that were meant to measure three main areas, which were cognitive knowledge of AI tools, practical competence in the use of such tools, and ethical understanding of their implication on business practice. These dimensions were defined in terms of different sets of questions related to awareness, the use of tools, and ethical considerations in line with the theoretical framework developed in Section 2.1.

3.3. Sampling

A purposive sampling strategy was employed to ensure the selection of information-rich participants who could provide meaningful insights into AI adoption in Thai enterprises. The participants had to have a significant level of professional experience, which would be between six and eleven years of experience or more, thus guaranteeing them the necessary exposure to organizational practices and technological changes (Ghosh, 2025). The sampling plan was made to balance the sector, with about 40 per cent of the sample in manufacturing, 30 per cent in information technology, and 30 per cent in corporate services; this was to represent the variety of contextual issues and artificial intelligence application. This method allowed the consideration of various views and still maintained attention to those participants, whose experience was directly related to the research goals.

3.4. Data Analysis

A systematic thematic analysis was performed on the data, using NVivo to code it and manage themes. The familiarization was made by means of the repeated verification of the interview summaries and responses to the survey. The research objectives have informed initial coding whereby codes like, skill gaps, training effectiveness, generational resistance and ethical concerns were yielded. These codes were further narrowed down and combined in bigger thematic units and included; generational and role specific divides, practical and theoretical training needs, HR as change agents and access and infrastructure barriers. Descriptive statistics were used to measure trends in the survey data, such as the percentage of participants who reported moderate AI knowledge (about 60% on average) or a particular skill gap (Sposato, 2025). The combination of quantitative and qualitative results helped to have a more thorough explanation of the prevalence of the identified patterns, as well as the rationales behind them, which guaranteed that the analysis reflected the statistical trends as well as the contextual details.

3.5. Ethical Considerations

This study adhered to rigorous ethical standards throughout its execution. Informed consent was obtained from all participants, with clear communication regarding the study's purpose, procedures, and intended use of data. The participants were also guaranteed their voluntary participation and had the freedom to drop out at any point without reprisal (Ben Ghrbeia & Alzubi, 2024).

Anonymity and confidentiality were maintained through de-identifying the personal and organizational information in all personal records and publications. Data were kept safely according to the institutional requirements and only research team had access to data. These measures ensured the protection of the rights of participants and high integrity of the research process. There are various limitations, which should be taken into account when interpreting the findings (Arnaud et al., 2025). To begin with, the use of self-reported data implies the possibility of social desirability bias, which means that participants can either exaggerate their proficiency in AI or report disadvantages.

Second, the qualitative sample, despite its insight the sample size was quite small (n = 21) and might not represent all Thai enterprises. Third, the discussion is centered on the particular industries and the Thai setting which makes it very difficult to generalize the results to other industries or cultures. In this way, summaries made with NotebookLM, though effective, might have missed some nuances that transcripts made verbatim would have recorded. Notwithstanding these shortcomings, the mixed-method design of the study and data triangulation increase the validity and richness of the results.

4. Analysis and Discussion

4.1. Demographic Profile

The sample consisted of an eclectic group of participants, representing Thai businesses, which has provided a rich contribution at the organizational levels and functions (Arnaud et al., 2025). The survey respondents (n = 294) were mostly representatives of large organizations (larger than 500 employees) (60%), and the distribution of sectors was mostly biased toward manufacturing (40%), and information technology (30%). Such distribution of organizational sizes is also interesting, and larger firms tend to have more resources to implement AI and face more complicated transformation issues.

Most of the respondents indicated that they have a lot of professional experience with about half of them having an experience that is over eleven years in their respective fields. This experience is pivotal, as it will support the ability of the participants to provide longitudinal perspectives on the change in the organization and the adoption of technology. These levels of experience were reflected in the qualitative interview sample. Table 1 provides the demographic data of the research participants. The sample will include respondents who work in various organizations of different sizes, sectors, experience and job position, and this will give a heterogeneous mix of the workforce, which makes the findings to be applicable to a wide range of organization settings.

Table 1. Participant demographic profile. Source: Author's survey data (2025).

Category	Subcategory	Frequency	Percentage
Organization size	>500 employees	176	60%
	201 - 500 employees	59	20%
	<200 employees	59	20%
Sector	Manufacturing	118	40%
	Information technology	88	30%
	Corporate services	88	30%
Experience	11+ years	147	50%
	6 - 10 years	88	30%
	1 - 5 years	59	20%
Role	Employees	206	70%
	HR/Managers	59	20%
	Trainers	29	10%

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The demographic distribution of the respondents is shown in Figure 1. The figure shows a heterogeneity regarding the size of the organization, industry, and level of experience, and job position, hence a representative and diverse sample. This kind of heterogeneity increases reliability and the generalizability of the study results. Most of the respondents had vast work experience levels as half said that they had more than eleven years working in their fields. This is a critical level of experience since it refers to those individuals that have witnessed organizational changes and can provide longitudinal information about the adoption of technology. The qualitative sample of the interview included participants with the age range of between 26 and 47 years and involved a heterogeneous group of occupations, namely law, graphic design, consulting, and human resources, which guaranteed a comprehensive representation of the views within the functional area of organizations. Figure 2 provides an exact picture of the demographics of the participants based on such important variables as the size of the organization, their industry and experience, and job titles. The distribution shows a balanced composition of respondents and thus the insights will show the views of various organizational

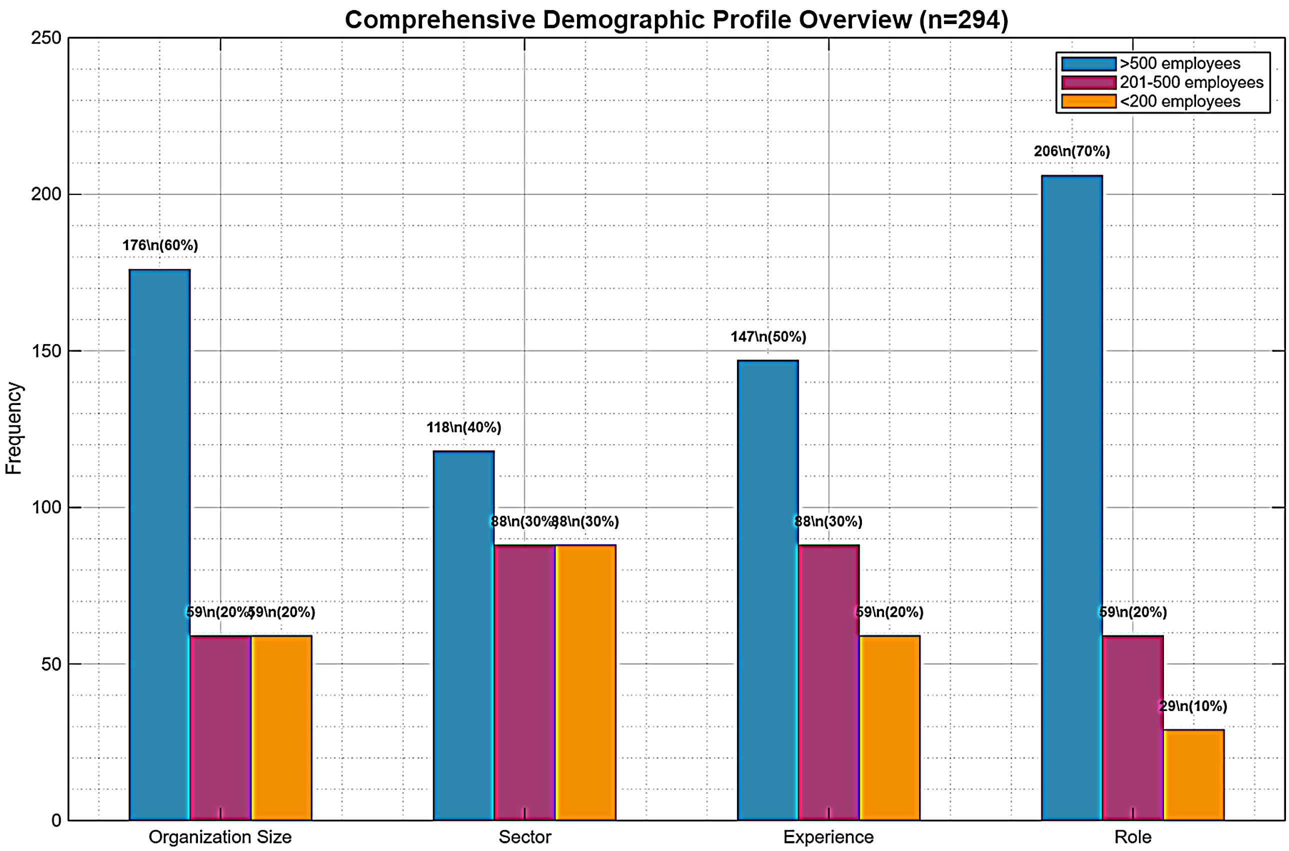

Figure 1. Demographic profile of study participants (n=294). Source: Author's own survey data (2025).

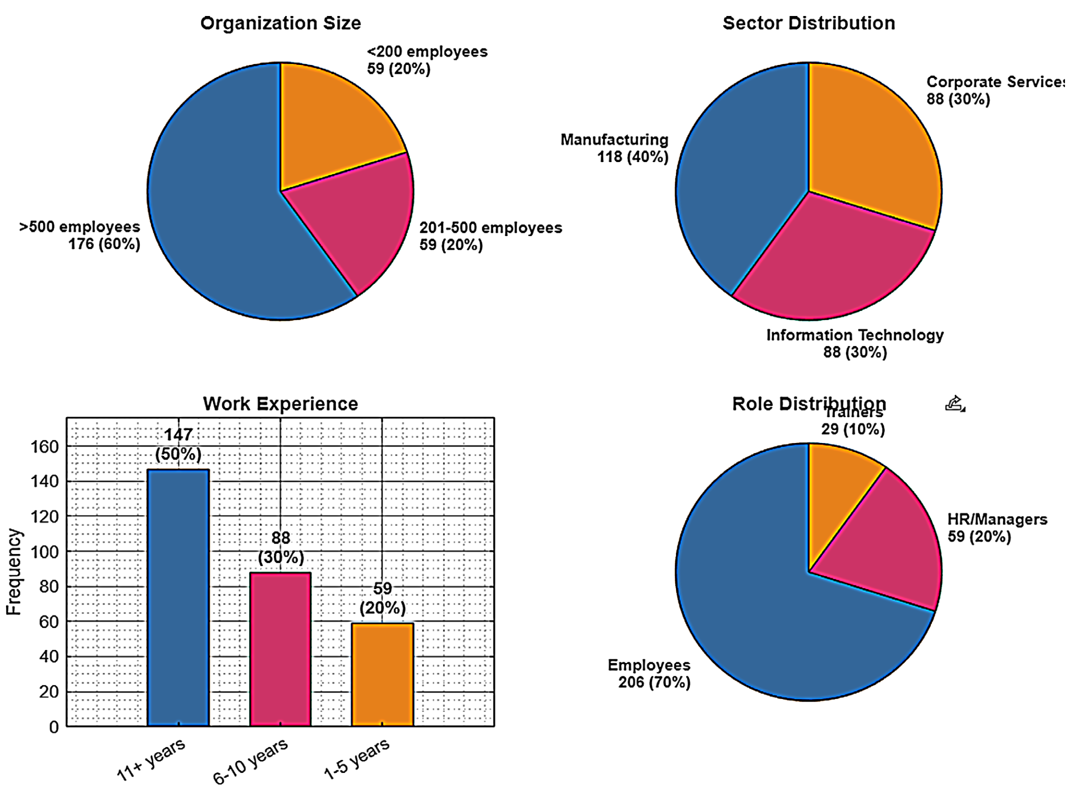

Figure 2. Comprehensive demographic profile overview. Source: author's own survey data (2025).

situations. The heterogeneity of the representation increases the validity of the study; it implies inclusion of the trends among older and younger professionals. The sample of qualitative interview respondents was aged between 26 and 47 years and constituted an eclectic group of occupations, such as law, graphic design, consulting, and human resources; the variety of the sample gives a complete account of views related to different functional areas of the organization.

4.2. AI Literacy Levels and Awareness

The paper revealed an advanced topography in relation to the understanding of artificial intelligence among the Thai professionals. According to the results of the survey presented in Table 2, the level of AI literacy was moderate, with half of the participants saying that they are able to explain the general AI concepts. Organizational awareness, in its turn, turned out to be much greater, with forty percent of respondents admitting to being either very aware of AI initiatives in their respective companies.

Table 2. AI literacy and awareness levels.

Metric	Level	Percentage	Observations
Understanding	Comprehensive	15%	Mostly IT professionals
	Moderate	50%	Could explain general concepts
	Basic	35%	Limited to tool usage
Organizational awareness	Very aware	40%	Leadership and IT roles
	Somewhat aware	45%	Middle management
	Minimal awareness	15%	Operational staff
Confidence level	High confidence	25%	Regular AI users
	Moderate confidence	45%	Occasional users
	Low confidence	30%	Rarely use AI tools

Qualitative interview data also supported these findings. As an example, one may turn to a 26-year-old lawyer, Nithi Intawarat, who demonstrated the level of AI knowledge that she obtained at university. She has finished an AI course, she said, seven years ago, which provided her with a general awareness of the topic, and said she currently uses ChatGPT to write emails and proofread documents. Figure 3 represents the total rate of AI literacy and awareness among Thai specialists, highlighting the difference in the level of familiarity with AI technologies in different cohorts. The specified tendency makes the development of specific training interventions focused on the improvement of the competencies of the employees in artificial intelligence critical. In the basic tier, AI literacy can be broadly described as having a limited range of practical implementation, in which theoretical knowledge is largely accompanied by low-level support positivities like the writing of job-related material and checking of documentation.

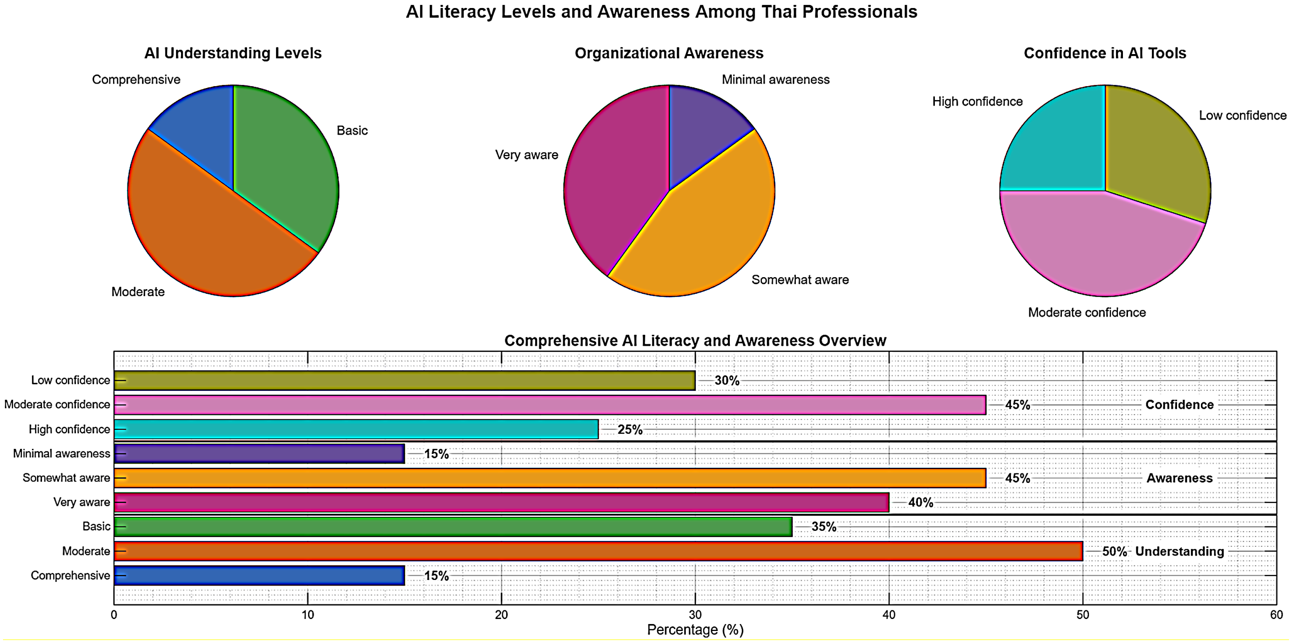

Figure 3. AI Literacy levels and awareness among Thai professionals. Source: primary data collected by the authors (2025).

On the other hand, some of the professionals showed a more proficient level of AI. In the case of a graphic designer, Khun Than, the use of AI technologies in his professional work received a rating of eight out of ten, which he explained by the consistent use of AI technologies in his work. He observed that AI systems have been widely used to support the generation of ideas and creation of visual content that resulted in significant improvements in productivity and time efficiency. This continued and ingrained use of AI in fundamental professional processes thus represents a high standard of AI literacy.

Figure 3 shows the level of AI literacy and awareness of the Thai professionals. In general, the importance of AI was well underlined, which can be also seen in 85 per cent of the respondents who stated that AI will be a key factor in the future of their industry. However, there is still present a visible disconnect between the reality of the importance of AI and the trust in its practical application, hence the need to go with more detailed, role-specific training programs.

4.3. Identified Skill Gaps

The research has found that there are a number of important skill shortages that hamper the successful implementation of artificial intelligence. The most obvious gaps as described in Table 3 are related to the practical use especially in areas like timely engineering and the use of agentic AI. Besides technical shortfalls, an important lack of knowledge in ethical awareness is noted in the AI literacy. Several respondents expressed their fears about the consequences of the artificial intelligence on data privacy and how AI algorithms are biased. In the Thai business environment, these issues are enhanced by the Thai data protection laws, including the Personal Data Protection Act (PDPA). These ethical concerns could be addressed by conducting special training on ethical practices in AI, which will help companies to reduce the risks and foster responsible use of AI.

Secondly, a serious gap has been determined, which has to do with the ethical considerations and data privacy, especially regarding the management staff. The most obvious gaps as described in Table 3, are related to the practical use especially in areas like timely engineering and the use of agentic AI. Besides technical shortfalls, an important lack of knowledge in ethical awareness is noted in AI literacy. Several respondents expressed their fears about the consequences of the artificial intelligence on data privacy and how AI algorithms are biased. In the Thai business environment, these issues are enhanced by the Thai data protection laws, including the Personal Data Protection Act (PDPA). These ethical concerns could be addressed by conducting special training on ethical practices in AI, which will help companies to reduce the risks and foster responsible use.

The combination of Table 3 and Figure 4 identifies the most significant AI skill gaps that were noted throughout Thai enterprises. The results indicate that practical implementation and technical inculcation have the greatest gaps especially among the non-technical and operational personnel. Another issue that is brought up is ethical knowledge, particularly in the management that needs to control data governance and responsible AI utilization. These gaps highlight the

Table 3. Identified AI skill gaps.

Skill category	Deficiency level	Affected roles	Manifestations
Practical application	High (65%)	All non-technical roles	Difficulty with prompt engineering, tool selection
Ethical understanding	Moderate-high (55%)	Management roles	Privacy concerns, bias recognition
Technical integration	High (60%)	Operational staff	API usage, workflow integration
Strategic implementation	Moderate (45%)	Leadership	ROI calculation, implementation planning

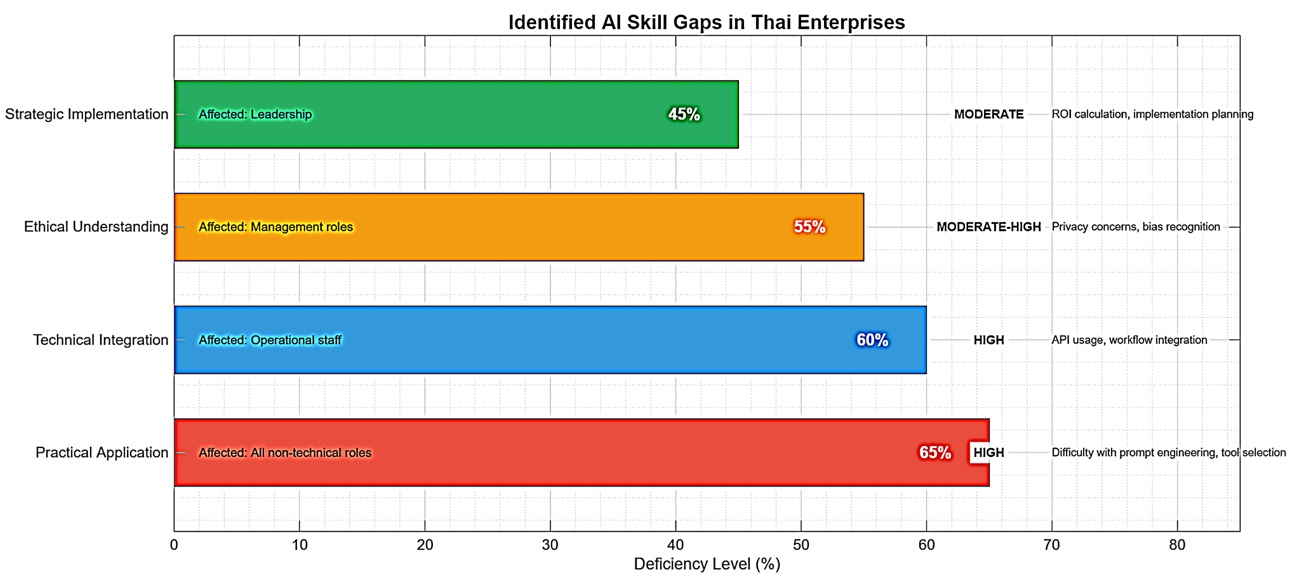

Figure 4. Identified AI skill gaps in Thai enterprises. Source: author's own survey data (2025).

real necessity of role-specific training programs alongside organization and structure so as to facilitate effective AI adoption.

Many employees were characterized by a lack of knowledge on high-level applications like predictive maintenance or those applications that automate certain back-office processes, thus presenting significant difficulties. Table 3 summarises the major gaps in AI skills which have been observed in Thai businesses with a focus on mastering the required skills practically, understanding the ethical issues, technical integration, and strategic implementation.

The following identified AI skill gaps are outlined in Figure 4 and it can be seen that the barriers to the practical implementation and technical integration were especially relevant. Besides, there was a clear generation gap between sectors. This was highlighted by a HR manager, Ms. Ratsanee Sapetch, who noted that the senior management staff tend to have reduced competencies in digital skills, thus creating a strong competence gap compared to the younger and more techno savvy staff.

The resultant imbalanced situation also affects not just the performance of individuals but also the dynamics of a team and the ability of the organization to be innovative in its capacity. Therefore, the skill-gap analysis showed that the theoretical understanding of the concepts of AI was quite solid, and the practical abilities of implementation were limited. Only a quarter of respondents stated that they feel confident in designing AI-enhanced workflows, with about 60 percent of them saying that they need to receive training centered on the practical use of the tools, as opposed to the abstract conceptualization.

4.4. Training Programs and Implementation

The training methods used by organizations in order to eliminate skill gaps included different methods. The majority of the programs focused on the basic ideas of AI and generative applications like ChatGPT and Perplexity, often with industry-specific case studies, as seen in Table 4.

Table 4. Training program characteristics.

Program aspect	Characteristics	Prevalence	Effectiveness
Content focus	Basic concepts (70%)	High	Moderate
	Generative AI tools (60%)	High	High
	Industry applications (45%)	Moderate	High
Delivery method	Workshops (65%)	High	High
	Online courses (40%)	Moderate	Moderate
	Coaching sessions (35%)	Moderate	High
Assessment	Participation tracking (80%)	High	Low
	Skill testing (45%)	Moderate	High
	Impact measurement (25%)	Low	High

Programs were generally structured in needs-based model and incorporated in organization training matrices. Techniques of delivery were focused on practical workshops and coaching exercises, the technologies of ChatGPT helped simulations were integrated into the practical ones. Trin, a freelance AI consultant described his approach: I am only interested in department-specific applications. We do content generation in marketing teams and process optimization in operations. Role relevant applications have the greatest learning outcomes. The way assessment was done in different organizations differed significantly (Schiuma et al., 2024). Where 80 percent of them followed participation rates (only) 45 percent of them carried out skill testing and only 25 percent of them evaluated business impact. This gap in assessment can be seen as a great opportunity to enhance training evaluation practice. The most successful programs were those that had the feature of an ongoing rather than event-based structure, included practical exercises that were applicable in day-to-day work and post-training support mechanisms. Programs that had combined theoretical learning with instant practical implementation showed the best knowledge retention and implementation.

4.5. Challenges and Management Strategies

The implementation was fraught with a lot of difficulties that required new management approaches. As shown in **Table 5**, the most mentioned barriers were budget limitations (cited by 65 percent of the organizations sampled), engagement challenges (60 percent) and the presence of strong differences in the level of literacy among employees (75 percent).

Table 5. Implementation challenges and solutions.

Challenge	Prevalence	Impact level	Mitigation strategies
Budget constraints	65%	High	Internal trainers, phased implementation
Engagement issues	60%	Moderate-high	Relevance demonstration, leadership support
Skill variance	75%	High	Tiered training, peer mentoring
Technical barriers	55%	Moderate	Equipment provision, IT support

Internal champions are critical players in the marketing of artificial intelligence in the organizational set ups (Schiuma et al., 2024). These agents are chosen according to their proven abilities in fields of artificial intelligence and they serve as mentors and inspirers of their colleagues. Companies can empower such champions by equipping them with specific training materials and leadership prospects, therefore, allowing them to mentor others doing work related to AI. The peer-to-peer learning scheme creates an inclusive environment in the adoption of technology, hence making the shift to AI adoption easier. Enterprises can institutionalize a group of internal champions, who will accelerate the uptake of AI tools, by systematically indexing workers who possess an advanced level of competency in

AI tools and predisposition towards pedagogy. By encouraging internal champions to hold training, workshops, or informal learning groups, it becomes possible to reduce the impact of resistance and increase the level of employee trust in the application of AI. This type of approach does not only accelerate the adoption curve, but also creates a culture of continuous learning.

4.6. Impacts of AI Literacy

The demonstrated benefits of AI literacy were substantial across multiple dimensions, as detailed in Table 6. Productivity improvements were particularly notable, with 70% of respondents reporting time savings in routine tasks.

Table 6. Impact assessment of AI literacy.

Impact area	Significance level	Manifestations	Supporting evidence
Productivity	High (70%)	Time savings, error reduction	40% reduction in routine tasks
Career development	High (65%)	Promotion opportunities, skill recognition	50% report career impact
Innovation	Moderate-high (60%)	New solutions, improved processes	35% innovation increase
Organizational growth	High (75%)	Efficiency gains, competitive advantage	60% growth correlation

Career effects were massive considering 50 percent of the respondents stated that AI skills have had a huge effect on their career development. The relationship between organizational growth and AI skills was steep, with 60 percent of them indicating that it is very crucial to organizational growth and 70 percent confirming that it is fundamental to the leadership position (Veseli et al., 2025). In qualitative findings, more subtle benefits were highlighted that were not metrics based. As an example, Khun Than showed how AI technologies transformed the creative process: What used to take hours of brainstorming now takes minutes. The AI will not replace our creativity but instead enhance its power that will help us to consider more ideas and provide better results to clients. In addition, the research pointed out the secondary benefits such as better collaboration (as noted in 45-percent of the teams that used AI tools), better problem-solving skills (55-percent), and employee satisfaction (40-percent of the surveyed teams said they felt more content with their jobs as a result of reduced tediousness).

4.7. Thematic Insights from Interviews

One assistant HR manager who is aged 50 years said, it is hard to convince senior employees to use artificial intelligence. They are more at ease with conventional methodologies. In the meantime, a 27-year-old software developer said, “In my case, AI assistants like ChatGPT are part of daily business, and I cannot imagine doing my job without them. These opposing opinions can be seen as the example of the generational gap in adopting AI, and older workers would tend to need more assistance in maintaining the skills gap. Being brought up with the digital tools, the younger generation can find it easier to incorporate AI into their day-to-day operations, though the older employees require more formal training and guidance to overcome their opposition or their unfamiliarity with the technologies. The qualitative analysis revealed five central themes that provide depth to the quantitative findings:

Theme 1: Spectrum of AI Literacy and Motivation: Participants displayed a wide range of AI proficiency levels. At the foundational level, Nithi Intawarat represented employees with a basic understanding: "I have enough knowledge to use simple tools but need more training to really adapt AI to my legal work." At the advanced level, Khun Than demonstrated sophisticated application: "We're not just using AI tools, we're integrating them into our entire creative workflow (Shatila et al., 2025)." The universal motivation for learning stemmed from practical needs rather than theoretical interest, with most participants seeking job-specific applications.

Theme 2: The Central Role of Structured Training: HR-led initiatives emerged as crucial drivers of AI adoption. Ms. Sapetch detailed their approach: "We started with managers because they need to understand and champion AI adoption. The training focused on practical ChatGPT applications for their specific management tasks." Measurable benefits included time savings (30-50% on routine tasks) and improved output quality. Trainers emphasized practical methodology; Mr. Trin noted: "I show immediate practical applications of how AI can save them time today, not theoretical benefits for tomorrow."

Theme 3: Addressing the Skill Gap: The generational divide presented particular challenges. Older employees often struggled with both technical aspects and mindset shifts. Creative solutions emerged, including "reverse mentoring" where younger staff trained senior colleagues, and internal expert networks that provided ongoing support (Meena & Santhanalakshmi, 2025). One organization created "AI champions" in each department who received advanced training and supported colleagues.

Theme 4: Practical Adoption Challenges: Resource limitations significantly hindered implementation. Many employees lacked adequate hardware or software access. User experience issues also emerged, particularly for less tech-savvy users. Nithi suggested: "AI tools need to be more user-friendly, especially for older generations. The learning curve can be steep without proper design consideration."

Theme 5: Future Vision and Integration: The participants projected advanced AI integration in areas that were not in use. Mr. The future training Trin predicted: "Future training will focus on implementing AI alongside process re-engineering, but not on the use of tools alone but on redesigning workflows around AI capabilities. The vision of automation was centered more around content workflows and decision-making procedures, and it was no longer task specific (Rêgo et al., 2024). The study proves that the process of AI adoption in Thailand presents serious challenges including the skill formation and the distribution of resources but the high motivation of the professionals and the new best practices can offer a solid base to successful transformation in the organization. The nexus of the technical capability building and the organizational change management is the key discriminating factor in the success of AI implementation.

5. Results

5.1. Descriptive Statistics

The questionnaire got 294 responses including valid surveys, but in this case, the questionnaire was sent to professionals working in different Thai enterprises to provide a strong empirical data that could be analyzed further. The subsequent findings summarize demographics, attitudes towards artificial intelligence literacy, and the current situation of AI training programmes in organisations, which were supported with the help of the given tables and figures. A demographic profile of the participants is provided in **Table 7** according to the industry sector, the organisational size, and the role in a department. The most represented sector was the Manufacturing one with 118 respondents (40-percent). Information Technology (88 respondents, 30 %) then came next followed by Corporate Services (88 respondents, 30 %). When it comes to organisational size, the group of organisations that hired over 500 employees presented the most significant cohort (176 respondents, 60 näxible representation of large organisations). Most of the respondents have high levels of experience in their professions with half of them having 11 or more years in their respective fields. It was found that the most common occupational category was the employees (206 respondents or 70 per cent), and then the HR/Managers (59 respondents or 20 per cent), and finally the trainers (29 respondents or 10 per cent).

Table 7. Demographic profile of participants (n = 294).

Category	Subcategory	Frequency	Percentage
Organization size	>500 employees	176	60%
	201 - 500 employees	59	20%
	<200 employees	59	20%
Sector	Manufacturing	118	40%
	Information technology	88	30%
	Corporate services	88	30%
Experience	11+ years	147	50%
	6 - 10 years	88	30%
	1 - 5 years	59	20%
Role	Employees	206	70%
	HR/Managers	59	20%
	Trainers	29	10%

Most of the interviewees had long work experience, half saying that they had over eleven years of experience in the fields. This experience is paramount because it represents a group of practitioners that have lived through organizational change and can provide longitudinal data about technology adoption. The qualitative interview group was aged between twenty-six and forty-seven years and targeted a wide range of professional specialties, such as law, graphic design, consulting, human resources, so that the process guaranteed a broad range of organizational functions.

5.2. Hypothesis Testing

ANOVA Testing (Level of significance = 0.05)

Inferential statistical methods such as Analysis of Variance (ANOVA) allow the researcher to determine whether statistically significant differences exist between the means of three or more independent groups. In the current study, a one-way ANOVA test was used to test the null hypothesis and ascertain important group differences with a level of alpha of.05. ANOVA is still a powerful tool in the comparison of more than two groups, which will allow to define whether the observed differences in the mean have reached a level of statistical significance (Tabachnick and Fidell, 2013). Normality and homogeneity of variance assumptions were checked before the analysis was done. The data were then processed as it was and ANOVA was then performed on the variable of interest.

Hypothesis 1:

There is a significant difference in the perceived criticality of AI literacy for organizational growth based on the respondent's industry sector (Luthfia et al., 2025).

Table 8 displays the descriptive statistics for Hypothesis 1. Perceived criticality of artificial intelligence literacy to organizational growth was the dependent variable, which was operationalized at a five-point Likert-type scale that ranged between the response of moderately critical and absolutely critical. The mean score was also high (M approaching 4.2 in a 5-point scale, SD equal to 0.88), which means that there has been a strong agreement on the significance of AI literacy. However, mean scores vary among sectors, which suggests that perceptions may differ among various sectors.

Table 8. Descriptive statistics for H1 (Perceived AI criticality by industry).

Group (Industry)	n	M*	SD
IT/Technology	88	4.52	0.68
Manufacturing	118	4.19	0.83
Corporate services	88	4.07	0.92
Total	294	4.20	0.88

*Scale: 1 = Not critical, 2 = Slightly, 3 = Moderate, 4 = Very critical, 5 = Absolutely critical.
A Levene's Test was carried out to assess variance homogeneity across groups. The result showed an F statistic of 0.85 and a p-value of 0.54, indicating that the assumption of equal variances was not violated and the data was suitable for ANOVA analysis.

Hypothesis 2:

There is a significant difference in confidence in using AI tools based on whether an employee has received AI training (Figure 5).

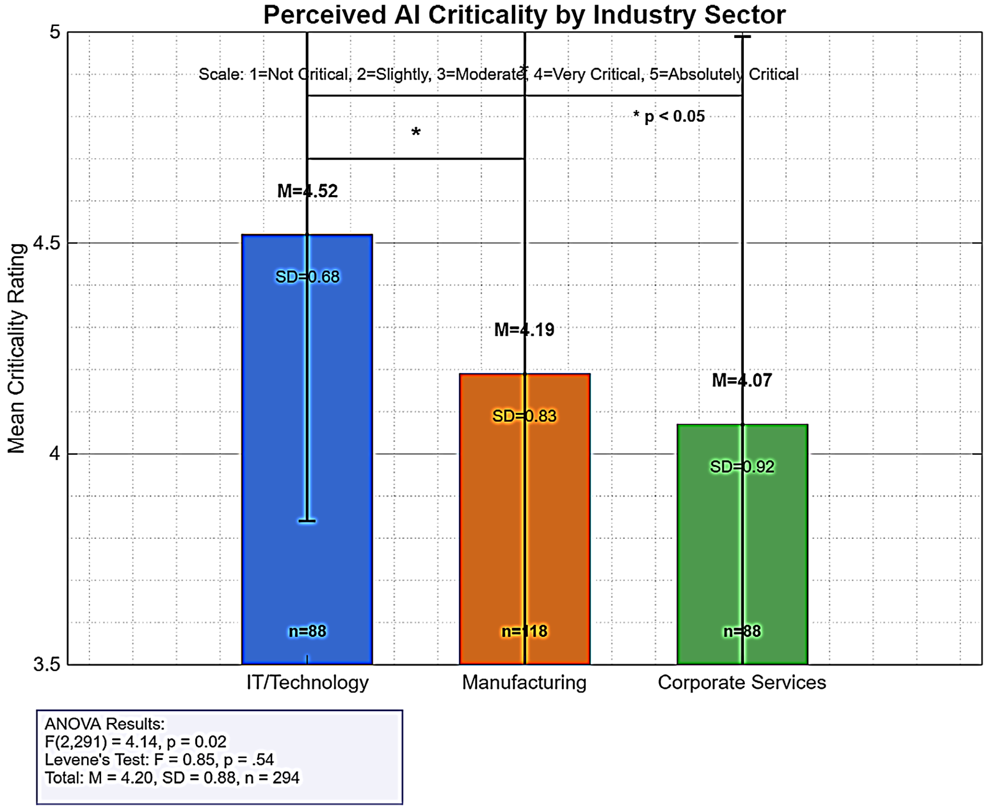

Figure 5. Perceived AI criticality by industry sector (ANOVA results: F = 4.14, p = 0.02). Source: author's own survey data (2025).

Table 10 summarizes the responses for Hypothesis 2. The analysis focuses on the categorical variable of AI training receipt ("Yes", "No", "Not sure"). The dependent variable is the confidence level in using AI tools relevant to one's role. The overall mean confidence score is moderate (M ≈ 3.2 on a 5-point scale, SD = 1.05).

The summary of the ANOVA results of the comparison of perceived AI criticality among the industry sectors is presented in Table 9 and Figure 6. The F-value is high (4.14, p = 0.2) which means that the perception of groups is significantly different. Comparison after the fact indicates that AI literacy is more important to the professionals working in the IT/Technology sector than in Manufacturing or Corporate Services. The results indicate that industries that are more exposed to digital show a greater understanding of the strategic value of AI.

One-way ANOVA showed the statistically significant difference between the groups (F (2, 291) 13.27, p < .001). To establish the specific groups that differed a post-hoc Tukey HSD test was done. The post-hoc test proved that the mean confidence score in the group of yes (M 3.64) was significantly more than the confidence score in the group of no (M 2.74) and the group of not sure/soon (M 3.09).

Table 9. ANOVA table for H1. Source: Author's own survey data (2025)

	Sum of squares	df	Mean square	F	p
Between groups	6.12	2	3.06	4.14	0.02
Within groups	216.78	291	0.74		
Total	222.90	293			

A one-way ANOVA revealed a statistically significant difference between the groups ($F(2,291) = 4.14$, $p = .02$). Post-hoc analysis using Tukey's HSD test indicated that the IT/Technology group ($M = 4.52$, $SD = 0.68$) reported significantly higher perceived criticality than both the Manufacturing group ($M = 4.19$, $SD = 0.83$) and Corporate Services group ($M = 4.07$, $SD = 0.92$).

Table 10. Descriptive statistics for H2 (Confidence by training status).

Group (training received)	n	M*	SD
Yes	147	3.64	0.93
No	118	2.74	0.99
Not sure/Soon	29	3.09	1.04
Total	294	3.22	1.05

*Scale: 1 = Not confident, 2 = Slightly, 3 = Moderately, 4 = Very, 5 = Fully confident. A Levene's Test statistic (F) was 0.41 with a p-value of 0.66, confirming the homogeneity of variances for the ANOVA.

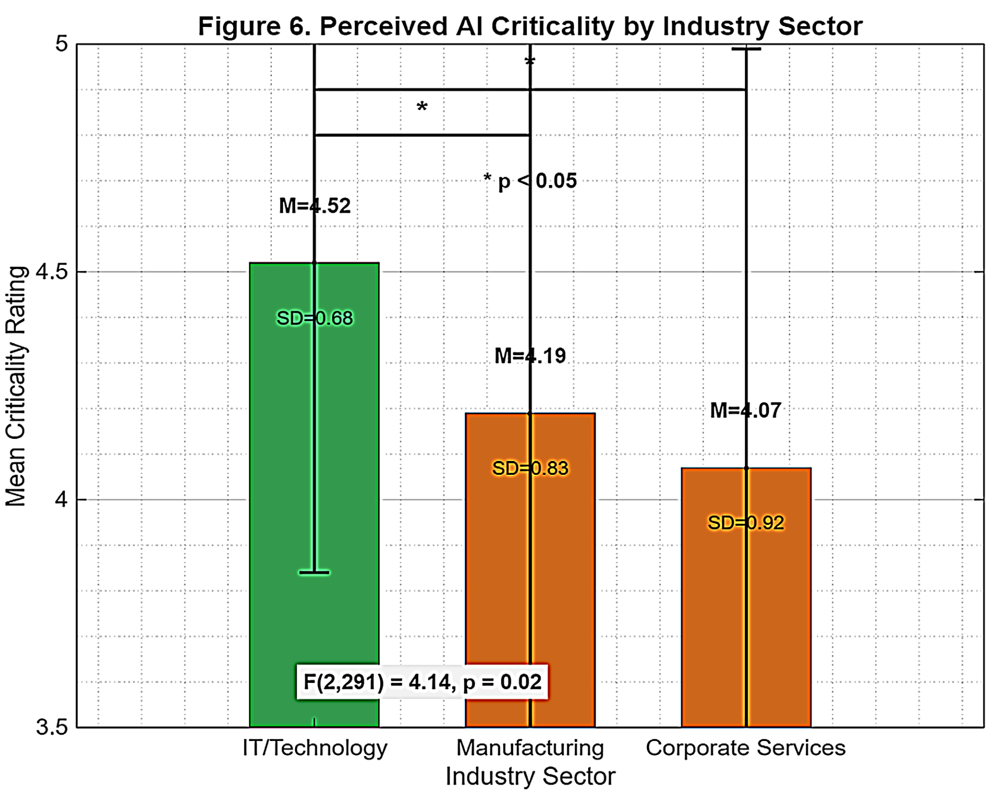

Figure 6. ANOVA results: Perceived AI criticality by industry sector. Source: author's own survey data (2025).

These findings offer strong empirical data to prove that formal training on AI is very effective in increasing the confidence of employees in the usage of AI tools. Therefore, the results indicate the empirical importance of the investment in AI upskilling programs in Thai companies (Table 11 and Figure 7).

Figure 7. Confidence in AI tools by training status. Source: author's own survey data (2025).

Table 11. ANOVA table for H2. Source: author's own survey data (2025).

		Sum of squares	df	Mean square	F	p
Between groups		24.97	2	12.49	13.27	<0.001
Within groups		274.99	291	0.94		
Total	299.96	293				

6. Discussion

6.1. Interpretation of Results

The results of this research indicate that AI literacy among Thai companies has a number of significant implications, which can be explained as supportive and adding to the current body of knowledge. Notions of the perceived criticality of AI literacy in all industry sectors (M ≈ 4.2/5) can be compared to the findings of reports by the World Economic Forum (2023) who highlight the growing relevance of digital competencies in the future labour market. This type of general awareness of the importance of AI implies that Thai organisations regardless of their sectoral affiliation value the opportunities that AI technologies can bring. This large variance of the confidence levels that depends on whether or not training was received ($F(2, 291) = 13.27$, $p < 0.001$) gives strong evidence of the Technology Acceptance Model, namely the perceived usefulness dimension. Those employees that were formally trained had significantly higher confidence ($M = 3.64$) than employees that were not trained ($M = 2.74$), which proves the statement that is practical exposure that enhances both the confidence and perceived utility of AI tools (Rêgo et al., 2024). A number of Thai-specific nuances were obtained on the basis of the data (Visutchiphol and Pankham, 2025). The focus on ease of use and the generational differences in the adoption of technologies indicate that cultural peculiarities are not so eminent in the Western context (Meena & Santha-nalakshmi, 2025). This observation builds up on the Diffusion of Innovations theory by Rogers (2003), by showing that, culture-specific components in the emerging economies shape the pattern of technology adoption.

6.2. Practical Implications

To the HR practitioners, this data highlights the need to make the human resources departments to develop and execute tailored, practical training programs that address unique organizational requirements. A group of 147 trained staffs showed significantly higher levels of confidence ($M = 3.64$), which implies that organizational focus should be on role-specific applications that may be implemented immediately, as opposed to presenting generic artificial intelligence overviews. Moreover, the HR professionals are advised to locate and mobilize internal champions who can support the adoption of AI and influence others through peer influence and success stories, especially since about and 11 years old people occupied more than 11 years of experience and could potentially serve as successful change agents.

To organizational leaders, the evidence recommends that the executives should be proactive in supporting AI initiatives and institute enabling cultures, where people are not afraid of making mistakes. It has been observed that executive approval seems to be a decisive factor of successful AI adoption particularly considering the fact that companies that had more than 500 workers (60% of the sample) showed a higher rate of AI adoption (Luthfia et al., 2025). The leaders are expected to invest in lifelong learning activities and to build systems that can help spread best practices across departments, specifically between the technical (IT/Data Analytics) and the non-technical operations.

In the case of trainers, the empirical results are clearly in favor of the use of practice-oriented, application-oriented, pedagogical approaches. Teachers need to move away more theory-based tools into more practical workshops that use tools that are relevant to the daily activities of employees. The large reliability coefficient (Cronbach 0.89) of the perception measures will show that training strictly designed produces consistent improvements in employee attitudes toward artificial intelligence, which is specifically relevant due to the heterogeneity of the sector (40% of the respondents in Manufacturing, 30% in IT and 30% in Corporate Services) and, consequently, the need to train employees through individualized methods.

6.3. Theoretical Contributions

This research has multiple valuable theoretical implications on the adoption of technology and digital literacy literature (Le et al., 2024). It builds on Technology Acceptance Model by adding qualitative variables that are unique to the use of AI, in particular, the influence of the cultural dimensions in the context of emerging market. The statistically significant difference in the perceived criticality between industry sectors ($F(2, 291) = 4.14$, $p = 0.02$), with the largest ratings in IT/Technology ($M = 4.52$) offer a subtle insight into the impact of industry context on technology perception. The study offers an in-depth paradigm of interpreting AI literacy that includes technical skills and organizational dynamics and advances the conceptualization of the AI literacy by Long and Magerko (2020) (Kraiwanit & Terdpaopong, 2024). The validity of this framework is enhanced by the large sample size ($n = 294$) of the study in various sectors and sizes of organizations. It also provides comprehensive empirical data on the Thai case, which has a large gap in the literature on the use of AI in the emerging Southeast Asian countries. This paper also illustrates the role that generational differences and user-friendly issues play in relationship-based, hierarchical cultures in particular in influencing technology adoption and plays a part in a more detailed comprehension of how culture influences technology adoption. The results that 70 percent of the respondents were ordinary employees give valuable information regarding the application of AI at operational levels and not only managerial views.

The policymakers can support AI education by establishing national programs offering AI training and resources to enterprises of all sizes, but with special focus being on SMEs situated in rural areas. These are likely to close the digital divide and create a more inclusive workforce. Moreover, policymakers ought to encourage organizations to educate their workforce in AI literacy by providing tax exemption or subsidies on AI upskilling programs, which will not only spur national growth but also promote creativity in the field of AI applications.

6.4. Limitations and Future Research

Although this research produces meaningful ideas on AI literacy and skills gaps among Thai companies, there are limitations that need to be mentioned. To start with, the sample of 294 respondents, though representative, might not be representative enough in the sense of the experiences of smaller businesses or less technologically developed industries. The research mainly focuses on bigger organizations, which can lead to bias in the results to more technologically advanced settings. The gap noted in future studies must be filled by involving a wider range of industries such as small and medium-sized enterprises (SMEs) in the rural areas. Thus, the sample of the qualitative interview ($n = 21$) is not very large and the results might not be fully reflective of the overall views at all ages and all sectors and areas in Thailand. The future research should expand the sample and look into the impact of cultural elements more closely, especially in specific regions of Thailand where digital literacy can differ. On the other hand, second limitation is related to the cross-sectional nature of the study that gives a cross-sectional view of AI literacy at one location over time. The future studies may take the form of a longitudinal study to assess the effectiveness of AI training programs in the long term and monitor the change in AI implementation and organizational change as time goes by. However, the mechanisms in the field of AI literacy that need to be addressed in future studies include sector-related issues and the importance of AI literacy on the business performance indicators, to comprehend the real value of AI in organizational change.

7. Conclusion

As the current research shows, AI literacy is a key driving force of organizational change in Thailand; the process of its evolution requires the consideration of various interconnected issues. The analysis supports several major findings that were made out of the investigation of 294 professionals of the various Thai enterprises: AI literacy is unanimously considered important in any industry sector ($M = 4.2/5$), and IT/Technology professionals agree with this idea ($M = 4.52$). Formal training also increases the confidence of employees with AI tools significantly (trained employees have statistically significant higher levels of confidence ($M = 3.64$) compared with untrained colleagues ($M = 2.74$), the difference is significant ($F (2, 291) = 13.27$, $p = 0.001$).

It is not only the technical implementation, but also the issue of culture and the organization. Results show that the generation gap and the issue of user-friendliness is a unique characteristic that determines the adoption of technology in the Thai environment, as one out of five participants who has 11 years or above experience may face greater challenges in adapting to the technology. The complex AI literacy issue requires a multimodal approach that would aim at tackling the technical skills, cultural obstacles, and the organizational frameworks at the same time.

Based on these findings, there are evidence-based recommendations which we suggest. Organizations should also ensure they introduce continuous, hands-on training programs where practical application should be given more importance than theoretical training given that 60 percent of respondents were representing large organizations (more than 500 employees) that have more resources available to implement them. Training programs must be scaled to suit specific generational groups and occupations, and special attention should be paid to the need to increase the user-friendliness among the employees with a low level of technical skills. In addition, firms ought to create inclusive learning opportunities that should promote knowledge spread among staff members of different ranks, and the rationale is that 70 percent of them are ordinary employees who can beneficially gain through peer learning systems. Based on our results that only a quarter of organizations currently measure the effectiveness of training, the human resources departments should develop metrics to measure the effect of AI training on employee confidence and organizational results. The leadership should make visible support of AI initiatives and provide safe areas of experimentation and learning to promote a culture of innovation and continuous improvements, which is necessary since manufacturing (40 percent of the sample) and corporate services (30 percent of the sample) might require specific implementation approaches.

There are a few restrictions that should be mentioned. The sample used (294 people) gives strong results, but future research should extend its boundaries to include the variety of organizational types and sizes. The cross-sectional design provides a viewpoint but excludes the possibility of tracking the changes of attitudes and practices as AI technologies grow and organizational abilities emerge. Therefore, longitudinal designs are justified to track the long-term effectiveness of AI training programs and analyze the nexus of AI literacy and concrete organizational performance, such as the metrics of productivity, the rate of innovation, and positioning.

The study ought to be extended with respect to sector-specific differences in AI adoption trend especially by comparing manufacturing (40 percent of the sample), information technology (30 percent), and corporate services (30 percent) sectors that formed the samples. In addition, research should explore the impact of cultural elements on the adoption of AI in different Asian environments, thus contributing to the further development of the concept of the integration of AI into different cultural contexts. To be AI-literate is not simply a technical process; it is a pillar to the successful and sustainable organisational transformation in Thailand. With the country streamlining its stance in the world digital economy, a wholesome AI-literacy programme is beneficial and mandatory. According to the study, the full potential of AI can be fully utilised by the organisations and implemented in the context of Thai business environment by focusing on both technical and human aspects of the technology and taking into account the cultural peculiarities of Thai environment. To digitally transform Thailand in the future and to provide human resources that can innovate and maintain a competitive edge in an ever-AI-based global economy, Thailand should develop AI literacy that is technologically advanced and culturally sensitive.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

References

Alhusban, M. I., Alshurafat, H., & Khatatbeh, I. N. (2025). Exploring Professional Perspectives on Integrating Generative Artificial Intelligence into Corporate Learning and Development: An Organizational Change Perspective. *Development and Learning in Organizations: An International Journal, 39,* 21-24. https://doi.org/10.1108/dlo-05-2024-0131

Arnaud, J., São Mamede, H., & Branco, F. (2025). The Relationship between Digital Transformation and Digital Literacy—An Explanatory Model: Systematic Literature Review. *F1000Research, 13,* Article 253. https://doi.org/10.12688/f1000research.146991.1

Ben Ghrbeia, S., & Alzubi, A. (2024). Building Micro-Foundations for Digital Transformation: A Moderated Mediation Model of the Interplay between Digital Literacy and Digital Transformation. *Sustainability, 16,* Article 3749. https://doi.org/10.3390/su16093749

Depoo, L., Hajerová-Mullerová, L., Kronberger, Z., Říhová, G., Stříteský, M., Hořáková, M., et al. (2025). Bridging the AI Gap: How Organizational Literacy and Individual Competencies Drive Implementation Success Across Industries. *Journal of Applied Technical and Educational Sciences, 15,* 1-21. https://www.jates.org/index.php/jatespath/article/download/400/189

Dittmar, E. C. (2025). AI as a Catalyst for Organizational Learning: Moving Beyond Tool Implementation to Learning Transformation. *Development and Learning in Organizations: An International Journal.* https://doi.org/10.1108/dlo-11-2024-0326

Ghosh, U. K. (2025). Transformative AI Applications in Business Decision-Making. In M. D. Baez (Ed.), *AI-Powered Leadership: Transforming Organizations in the Digital Age* (pp. 1-40). IGI Global. https://doi.org/10.4018/979-8-3373-1687-1.ch001

Jewapatarakul, D., & Ueasangkomsate, P. (2024). Digital Organizational Culture, Organizational Readiness, and Knowledge Acquisition Affecting Digital Transformation in Smes from Food Manufacturing Sector. *Sage Open, 14,* 1-15. https://doi.org/10.1177/21582440241297405

Kraiwanit, T., & Terdpaopong, K. (2024). Digital Transformation Model: The Study of the Governmental Agency in a Developing Country. *Journal of Governance and Regulation, 13,* 458-470. https://doi.org/10.22495/jgrv13i1siart18

Le, L. T. N., Jeenanunta, C., Ueki, Y., Intalar, N., & Komolavanij, S. (2024). The Role of Managerial Competencies in Driving Industry 4.0 Adoption: A Comparative Study of Thailand and Vietnam's Manufacturing Sectors. *Sustainability, 17,* Article 77. https://doi.org/10.3390/su17010077

Leal, D. C., Capetillo, A., & Castorena, D. G. (2025). AI Literacy and Proficiency: An Industry Reports Analysis to Achieve Educational Innovation and Organizational Change. In *2025 Institute for the Future of Education Conference (IFE)* (pp. 1-6). IEEE. https://doi.org/10.1109/ife63672.2025.11024731

Luthfia, A., Herwati, E., Rosidah, & Bismo, A. (2025). Digital Transformation and Sustainable Growth: Empowering Women Entrepreneurs in Msmes through Enhanced Digital Literacy. In *2025 19th International Conference on Ubiquitous Information Management and Communication (IMCOM)* (pp. 1-7). IEEE. https://doi.org/10.1109/imcom64595.2025.10857542

Meena, G., & Santhanalakshmi, K. (2025). Deconstructing Digital Transformation: A Multidimensional Analysis of Digital Literacy's Role in Shaping Human Capital and Driving Organizational Success. *ECONOMICS, 13,* 405-430. https://doi.org/10.2478/eoik-2025-0018

Muankaew, N., & Levermore, R. (2025). Digital Transformation in Thailand: Transformation Trends and Challenges from Complementary Resources in Pre-Digital Organizations. *Journal of Science and Technology Policy Management.* https://doi.org/10.1108/jstpm-07-2024-0289

Pandit, S., Sarkar, S. K., Barik, S., & Sahu, S. (2025). AI in Skill Development, Critical Thinking, Digital Literacy, and AI-Driven Job Preparation. In F. D. Mobo (Ed.), *Impacts of AI on Students and Teachers in Education* 5.0 (pp. 23-76). IGI Global.

https://doi.org/10.4018/979-8-3693-8191-5.ch002

Promma, W., Imjai, N., Usman, B., & Aujirapongpan, S. (2025). The Influence of AI Literacy on Complex Problem-Solving Skills through Systematic Thinking Skills and Intuition Thinking Skills: An Empirical Study in Thai Gen Z Accounting Students. *Computers and Education: Artificial Intelligence, 8,* Article ID: 100382. https://doi.org/10.1016/j.caeai.2025.100382

Rêgo, B. S., Lourenço, D., Moreira, F., & Pereira, C. S. (2024). Digital Transformation, Skills and Education: A Systematic Literature Review. *Industry and Higher Education, 38,* 336-349. https://doi.org/10.1177/09504222231208969

Rogers, E. M. (2003). *Diffusion of Innovations (5th ed.).* New York: Free Press. https://teddykw2.wordpress.com/wp-content/uploads/2012/07/everett-m-rogers-diffusion-of-innovations.pdf

Sararuch, S., Buabangplu, P., Nittayathammakul, V., Wannapiroon, P., & Nilsook, P. (2025). The 3D-POD Model for Ai-Driven Institutional Transformation and Graduate Employment Readiness in Thailand in Digital Era. In W. W. K. Ma, S. S. K. Cheung, C. Li, P. Prayadsab, & A. Mungwattana (Eds.), *Blended Learning. Sustainable and Flexible Smart Learning* (pp. 31-49). Springer Nature Singapore. https://doi.org/10.1007/978-981-96-8430-4_3

Schiuma, G., Santarsiero, F., Carlucci, D., & Jarrar, Y. (2024). Transformative Leadership Competencies for Organizational Digital Transformation. *Business Horizons, 67,* 425-437. https://doi.org/10.1016/j.bushor.2024.04.004

Shatila, K., Aránega, A. Y., Soga, L. R., & Hernández-Lara, A. B. (2025). Digital Literacy, Digital Accessibility, Human Capital, and Entrepreneurial Resilience: A Case for Dynamic Business Ecosystems. *Journal of Innovation & Knowledge, 10,* Article ID: 100709. https://doi.org/10.1016/j.jik.2025.100709

Sposato, M. (2025). Developing Digital Leadership Skills for AI-Driven Research Environments. In A. Mutawa (Ed.), *Impacts of Generative AI on the Future of Research and Education* (pp. 235-254). IGI Global. https://doi.org/10.4018/979-8-3693-0884-4.ch010

Ueasangkomsate, P. (2025). Empowering Thai SMEs through IT Competency, Digitalization and Digital Transformation for New Product Development. *Cogent Business & Management, 12,* Article ID: 2458758. https://doi.org/10.1080/23311975.2025.2458758

Veseli, A., Hasanaj, P., & Bajraktari, A. (2025). Perceptions of Organizational Change Readiness for Sustainable Digital Transformation: Insights from Learning Management System Projects in Higher Education Institutions. *Sustainability, 17,* Article 619. https://doi.org/10.3390/su17020619

Visuthiphol, S., & Pankham, S. (2025). Artificial Intelligence-Enabled Decision Making in Social Media Adoption for Sustainable Digital Business in Thai SMEs. *Decision Making: Applications in Management and Engineering, 8,* 333-347. https://dmame-journal.socialspacejournal.eu/index.php/dmame/article/download/1366/287