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Factors affecting the perceived usefulness and intention to adopt artificial intelligence in manufacturing enterprises in the Southeast region of Vietnam

Giao Thi Phuong Lan[1], Pham Ngoc Khanh[2*]
[1]Industrial University of Ho Chi Minh City, Vietnam; lan@student.iuh.edu.vn (G.T.P.L.) phamngockhanh@iuh.edu.vn (P.N.K.).

Abstract: This study aims to explore "Factors affecting the perceived usefulness and intention to adopt artificial intelligence in manufacturing enterprises in the Southeast region of Vietnam." Based on an integrated framework combining the Technology Acceptance Model (TAM) and the Technology–Organization–Environment (TOE) model, this study analyzes how organizational, technological, and environmental factors influence the adoption of artificial intelligence (AI). By employing a mixed-methods approach—comprising expert interviews and a quantitative survey of 435 manufacturing enterprises—the data were processed using SPSS 29.0 and AMOS 29.0 through several steps: reliability testing, Exploratory Factor Analysis (EFA), Confirmatory Factor Analysis (CFA), and Structural Equation Modeling (SEM). The results reveal that five factors: government involvement (GI), perceived cost (PC), management support (MS), technical infrastructure (TI), and organizational culture (OC) positively influence perceived usefulness (PU). Meanwhile, competitive pressure (CP) and vendor partnership (VP) have a direct effect on the intention to adopt AI (AAI). Notably, perceived usefulness (PU) plays a significant mediating role and has a strong impact on the intention to adopt AI (AAI). These findings confirm the appropriateness of the TAM model in explaining AI acceptance behavior and provide managerial implications for business leaders and policymakers to promote AI adoption in manufacturing enterprises.

Keywords: *Artificial Intelligence, Influencing factors, Intention to adopt Artificial Intelligence, Manufacturing enterprises, Perceived usefulness, Southeastern Region.*

1. Introduction

Nowadays, Artificial Intelligence (AI) is becoming a critical competitive trend across various industries [1]. AI has been described as "a set of tools and technologies that can enhance and improve organizational performance" [2]. In several official statements, AI has also been referred to as a foundational component of the Fourth Industrial Revolution. Vietnam has made significant efforts to foster AI research, application, and human resource development in line with global AI development. Notable Vietnamese enterprises such as FPT, Viettel AI, VNPT AI, and VIN AI have achieved remarkable accomplishments in AI research and application, affirming the capabilities and international standing of Vietnamese engineers and experts in AI innovation [3].

The Vietnam Artificial Intelligence Day 2023 by AI4VN [4] with the theme "Vietnamese Enterprises in the AI Boom," brought together policymakers, business leaders, and experts to discuss the transformative potential of AI—one of the core technologies of the Fourth Industrial Revolution. They emphasized the growing applications of AI in enterprises and its potential to drive growth, enhance operational efficiency, and deliver greater customer value. However, despite its promise, AI adoption in Vietnam remains limited. Mr. Vu Trong Dao, deputy Director of VNPT AI, highlighted that only about 16% of Vietnamese enterprises have adopted AI, compared to 33% in Asia and 36–37% globally. He identified barriers such as user mindset, resistance to process change, and organizational

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* Correspondence: phamngockhanh@iuh.edu.vn

inertia as significant impediments to the adoption of AI by Ministry of Science and Technology [5].

Vietnam's AI development status is reflected in its global and regional rankings: in 2023, the country ranked 59th in AI readiness (5th in ASEAN); in 2022, the e-Government Development Index ranked Vietnam at 86th (also 5th in ASEAN); and the Global Innovation Index 2023 placed the country at 46th by Ministry of Science and Technology [6]. Resolution No. 34-NQ/TW, issued by the Politburo on October 7, 2022, outlined the strategic goal of developing the Southeastern region's economy, defense, and security until 2030 with a vision to 2045. It emphasized the establishment of new centralized IT zones in Ho Chi Minh City and the creation of a regional high-tech industrial cluster, particularly in the provinces of Dong Nai, Binh Duong, and Ba Ria-Vung Tau. These zones aim to attract investments in electronics, IoT, and AI production.

The successful implementation of AI in manufacturing enterprises is expected to enhance business strategies, increase productivity, minimize waste, improve product quality, and create added economic value. This calls for concrete strategies and plans to accelerate AI adoption Le Tan, et al. [7]; Nguyen, et al. [8] and Abaddi [9] suggest that enterprise leaders should promote innovation in business operations, strengthen managerial support, and invest in technological infrastructure to facilitate AI acceptance. Similarly, Jokonya and Bomvana [10] argue that policymakers must support the transition toward smart factories to boost productivity and competitiveness among small and medium-sized enterprises (SMEs).

The necessity of this research arises from the practical context of perceived usefulness and the intention to adopt AI among manufacturing enterprises in the Southeastern region and the growing academic interest in this topic. For instance, Jokonya and Bomvana [10] examined the determinants of AI adoption in food supply chains through a systematic review of over 50 peer-reviewed articles, revealing the nascent stage of this research and a lack of information on influencing factors. Chatterjee, et al. [11] investigated AI adoption in manufacturing firms using an integrated TAM-TOE model, collecting data from 340 employees across small, medium, and large organizations to examine technological, environmental, and social influences on Industry 4.0 adoption. Another study by Chatterjee, et al. [12] focused on AI-integrated CRM systems in Indian industries, analyzing 324 responses to assess security and privacy implications. Ghani, et al. [13] investigated AI adoption among 127 publicly listed manufacturing companies in Malaysia, targeting senior and middle managers to understand organizational and environmental influences. Abaddi [9] studied 537 SMEs across Jordan's service, manufacturing, commerce, and agriculture sectors, focusing on ownership and managerial perspectives. Kwak, et al. [14] explored the factors affecting SME executives' intentions to adopt smart factories in South Korea, surveying 175 participants to identify key determinants.

In Vietnam, domestic studies on AI adoption have also emerged. Le Tan, et al. [7] analyzed critical factors influencing AI in supply chain management in Da Nang-based SMEs, using survey data from 120 companies. Nguyen, et al. [8] Conducted a study with 193 senior managers in both public and private firms to assess factors affecting AI adoption. Chuyen, et al. [15] Explored the application of AI in agricultural supply chains, compiling secondary data from national and international sources to highlight influencing factors. Chi, et al. [16] Studied the impact of AI-powered chatbots on consumers' repurchase behavior in online retail, collecting 273 valid surveys in Hanoi and Quang Ninh. While these studies contribute to the literature, few have provided a comprehensive assessment of AI adoption in the Southeastern manufacturing sector. Therefore, this study focuses on identifying the factors that influence perceived usefulness and the intention to adopt AI in manufacturing enterprises in the Southeastern region of Vietnam.

2. Literature Review

2.1. The concepts of Artificial Intelligence (AI)

Artificial Intelligence (AI) emerged as an academic discipline in 1956, when both its name and mission were formally defined. The primary goal of AI is to enable machines to perform complex tasks that traditionally require human intelligence. Early research in AI was heavily influenced by philosophy, logic theory, and science fiction [17].

The concept of AI was first proposed at the Dartmouth Conference held in the United States in 1956 by Crevier [18]. Since then, AI has remained in the minds of researchers and gradually flourished within research laboratories. Beginning in the 2000s, and particularly after 2015, the rapid advancement of intelligent hardware (such as sensors and microchips), the development of algorithms, and the support of big data have significantly accelerated the evolution of AI technologies. Technologies such as natural language processing, machine learning, and deep learning have enabled the analysis of complex data sets, facilitating the management, planning, and operation processes across a wide range of industries by Kasemsap [19].

Today, AI has become a significant competitive trend in various industrial sectors by Davenport and Ronanki [1]. AI is defined as "a collection of tools and technologies capable of enhancing and improving organizational performance" by Alsheibani, et al. [2]. This is achieved by developing "artificial" systems capable of solving complex problems using "intelligence" that mimics human cognitive processes. The predictive insights provided by AI are crucial for strategic planning and have been effectively leveraged by enterprises to gain competitive advantages over their rivals by Varian [20].

2.2. The concept of Manufacturing Enterprises

A manufacturing enterprise is typically defined as a business organization engaged in the transformation of raw materials or components into finished goods through the use of labor, machinery, tools, and chemical or biological processing. These enterprises operate across various sectors—ranging from food and beverage, textiles, and electronics to heavy industries such as steel and machinery—and play a fundamental role in the industrial and economic development of a nation.

Manufacturing enterprises are characterized by structured production processes, the application of industrial technologies, and the management of supply chains, to achieve operational efficiency, quality control, and value creation. In the context of Industry 4.0, these enterprises are increasingly adopting advanced technologies such as automation, artificial intelligence (AI), and the Internet of Things (IoT) to enhance productivity, flexibility, and competitiveness in a globalized market.

2.3. Background theory

2.3.1. Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM), developed by Davis [21] proposes that an individual's attitude toward using a particular system is a key determinant of whether they will ultimately adopt or reject that system. According to the model, this attitude is primarily influenced by two core beliefs: Perceived Usefulness (PU) and Perceived Ease of Use (PEU). TAM was designed to explain user acceptance of technology by focusing on the end-user's perspective, emphasizing that both perceived usefulness and perceived ease of use are essential in determining an individual's intention to use and actual usage behavior.

(i)External Variables: These are factors that influence a person's beliefs regarding the acceptance of technological products or services. Such variables typically originate from two main sources: social influence processes and cognitive instrumental processes based on personal experience and perception by Venkatesh and Davis [22].

(ii)Perceived Usefulness (PU): Defined as "the degree to which a person believes that using a particular system would enhance their job performance" by Davis [21].

(iii)Perceived Ease of Use (PEU): Defined as "the degree to which a person believes that using a particular system would be free of effort" by Davis [21].

(iv)Attitude: Refers to an individual's positive or negative feelings about performing the target behavior. According to Ajzen and Fishbein [23] attitude is a critical factor that influences the success of technology implementation.

2.3.2. Technology - Organization - Environment Model (TOE)

The Technology–Organization–Environment (TOE) framework is one of the most widely utilized models for examining the adoption of new technologies within enterprises. Originally developed by Tornatzky and colleagues, this framework has been extensively applied to analyze the technology implementation process in organizational contexts. According to Tornatzky, et al. [24] the TOE model introduces three contextual factors—technology, organization, and environment—which collectively provide a robust foundation for understanding technological innovation in organizations. This multi-dimensional structure gives the TOE model an advantage over other technology adoption models in terms of capturing the value-creation process driven by technological innovation by Zhu, et al. [25]. A significant strength of the TOE framework is its flexibility; it is not constrained by organizational size or the specific characteristics of industry sectors. As such, it offers a comprehensive perspective on organizational technology adoption, encompassing the implementation process, associated challenges, and the broader impacts of technological innovation. Furthermore, the TOE framework helps to identify key determinants influencing an organization's capacity to adopt technology, categorized into three domains: technological, organizational, and environmental factors.

The technological context refers to both the internal and external technologies relevant to the firm. This includes the organization's existing technological infrastructure as well as emerging technologies available in the market. The organizational context encompasses elements such as firm size, degree of centralization and formalization, organizational complexity, human resource quality, and the availability of critical internal resources. The environmental context includes industry characteristics, competitive pressure, external resource accessibility, and interactions with regulatory policies and governmental initiatives by Tornatzky, et al. [24].

3. Research Hypotheses and Models

3.1. Research hypothesis

3.1.1. Government Involvement (GI)

Government involvement plays a crucial role in fostering innovation within the field of information technology by implementing appropriate strategies and support policies by Wang, et al. [26]. Governments can help facilitate the commercialization of emerging technologies by creating regulatory frameworks and well-structured policies. As noted by Al-Hawamdeh and Alshaer [27] the process of adopting new technologies is inherently complex and requires structured governmental support to ensure successful implementation. Prior research has shown that firms operating in environments with stronger regulatory presence and governmental engagement tend to exhibit a higher likelihood of adopting artificial intelligence technologies Ghani, et al. [13]. Governmental support not only establishes a conducive environment for AI adoption but also accelerates its diffusion and impact by Agrawal, et al. [28]. Based on these insights, the following hypothesis is proposed:

Hypothesis H_{1a}: Government involvement has a positive impact on perceived usefulness.

Hypothesis H_{1b}: Government involvement positively influences the intention to adopt AI among manufacturing enterprises in the Southeast region of Vietnam.

3.1.2. Competitive Pressure (CP)

Competitive pressure represents a key external factor driving emerging technologies' adoption. In industries characterized by intense competition—such as the automotive sector—companies are often compelled to integrate advanced technological solutions to satisfy customer expectations by Kamariah Kamaruddin and Mohamed Udin [29] and to maintain a strategic advantage in the marketplace by Lin, et al. [30]. However, the Indian automotive industry encounters numerous challenges, including abrupt changes in the global energy landscape, the rise of novel business models, stiff competition from international automobile brands, diminishing domestic market share, and underwhelming export performance. These conditions collectively restrict the sector's capacity for innovation and the uptake of new technologies by Van Bruggen, et al. [31].

Extensive empirical research has shown that firms pay close attention to their competitors' behaviors and strategies by Bhatia and Kumar [32] and Dai, et al. [33]. In the same vein, Bhatia and Kumar [32]

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offer empirical validation that organizations often respond to stakeholder demands including competitive pressures—when engaging in strategic actions related to environmental protection. Their findings suggest that such pressures can significantly impact the adoption of Industry 4.0 (I4.0) technologies, potentially resulting in improved sustainability outcomes. As a consequence, many businesses have begun integrating new technologies to align with sustainability goals and respond to the evolving competitive landscape by Agrawal, et al. [34]. Firms that delay the adoption of technological innovations risk falling behind competitors and may fail to meet performance and sustainability benchmarks by Bhatia and Kumar [32]. Drawing on this body of knowledge, the second hypothesis is proposed as follows:

Hypothesis H2a: Competitive pressure has a positive effect on perceived usefulness of AI.

Hypothesis H2b: Competitive pressure positively influences the intention to adopt AI in manufacturing enterprises in the Southeast region of Vietnam.

(iii) Perceived cost (PC)

The perceived cost associated with adopting new technologies includes both tangible financial expenses and intangible burdens such as time, effort, and system complexity by Kim [35] and Visschers and Siegrist [36]. These considerations can significantly influence an organization's willingness and ability to implement innovative systems. Visschers and Siegrist [36] examined the role that perceived costs and benefits play in shaping the value of AI-based decision-making tools within consumer contexts. In a similar vein, Antun, et al. [37] recognized the promising applications of deep learning in image reconstruction, but also noted that instability in AI performance can elevate the perceived cost of deployment.

Furthermore, Van Wynsberghe, et al. [38] brought attention to the broader economic and sustainability challenges tied to AI usage, pointing out its environmental footprint and social ramifications. Their work emphasized the importance of developing and deploying AI in a responsible and ethical manner. These hidden costs extend beyond energy use to include resource depletion, electronic waste, and the demand for supporting infrastructure. Solaiman [39] projected that the substantial financial investment required for training, evaluating, and implementing generative AI systems may restrict their use to a limited group of organizations with sufficient resources. Additionally, Thomas and Hedrick-Wong [40] highlighted that high implementation costs often involve training personnel, particularly within small and medium-sized enterprises (SMEs), where resources and technical expertise may be limited. Building upon these observations, the third hypothesis is proposed as follows:

Hypothesis H3a: Perceived cost has a positive effect on perceived usefulness.

Hypothesis H3b: Perceived cost has a positive effect on the intention to adopt AI in manufacturing enterprises in the Southeast region of Vietnam.

(iv) Vendor partnership (VP)

Empirical evidence highlights that partnerships with vendors play a vital role in driving innovation adoption by Sulaiman and Wickramasinghe [41]. Kuzma, et al. [42] identified a significant link between innovation especially through collaboration with suppliers and the achievement of sustainable performance results. In addition, Sahu, et al. [43] investigated supplier selection processes within the Indian automotive sector by applying an integrated Multi Criteria Decision Making (MCDM) framework. Drawing from these findings, the fourth hypothesis is formulated as follows:

Hypothesis H4a: Vendor partnership has a positive effect on perceived usefulness.

Hypothesis H4b: Vendor partnership has a positive effect on the intention to adopt AI among manufacturing enterprises in the Southeast region of Vietnam.

(v) Managerial support (MS)

Managerial support refers to the degree to which senior leadership promotes and allocates necessary resources to facilitate the adoption of technological innovations by Dong, et al. [44]. According to Haldorai, et al. [45] such support embodies the dedication and active participation of top executives in driving and nurturing innovation within organizations. Numerous studies across diverse settings have examined how managerial backing affects the willingness to adopt various technological innovations by

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Low, et al. [46] and Wong, et al. [47]. For instance, Hsu, et al. [48] investigated the interplay between openness to technology adoption, executive support, and service innovation within the context of social innovation and technology implementation. More recently, research by Lutfi, et al. [49] demonstrated that support from senior management plays a crucial role in enhancing the utilization of digital technologies among small and medium-sized enterprises (SMEs) in Jordan. Building on these findings, the fifth hypothesis is proposed as follows:

Hypothesis H5a: Managerial support has a positive effect on perceived usefulness.

Hypothesis H5b: Managerial support has a positive effect on the intention to adopt AI among manufacturing enterprises in the Southeast region of Vietnam.

(vi) Technical infrastructure (TI)

Technical infrastructure refers to an organization's access to suitable hardware, software, networking, and data resources necessary to support the implementation of technological innovations by Byrd and Turner [50]. It is recognized as an environmental factor that lays the groundwork and creates favorable conditions for technology adoption by Pan and Jang [51]. However, research findings on the impact of technical infrastructure on the intention to adopt different technological innovations have been mixed. For instance, Pillai, et al. [52] identified that factors such as compatibility, external pressure, perceived benefits, and vendor support promote adoption, while IT infrastructure and government support showed no significant effect. Conversely, Alghamdi [53] reported that communication channels, government regulations, market structure, and technical infrastructure significantly influence adoption decisions, whereas managerial backing and supplier partnerships did not have a notable impact. Such divergent results might be attributed to variations in industrial sectors and geographic contexts. Additionally, Joshi, et al. [54] examined technology adoption in India, focusing on price sensitivity, environmental concerns, infrastructure availability, and knowledge, with government policy serving as a mediating variable. Drawing from these observations, the sixth hypothesis is formulated as follows:

Hypothesis H6a: Technical infrastructure has a positive effect on perceived usefulness.

Hypothesis H6b: Technical infrastructure has a positive effect on the intention to adopt AI in manufacturing enterprises in the Southeast region of Vietnam.

(vii) Organizational culture (OC)

Organizational culture is essential for AI adoption as it fosters a variety of ideas and recommendations concerning systems and processes. It significantly influences employees' attitudes toward embracing AI and pursuing innovation. Organizations that cultivate an environment encouraging experimentation, openness to change, and willingness to take risks tend to be more receptive to AI technologies, thereby establishing favorable conditions for innovation and continuous learning. Likewise, strong leadership support is recognized as a critical factor in the successful adoption of AI, with senior executives playing a vital role in promoting AI initiatives, allocating necessary resources, and facilitating organizational transformation by Usman, et al. [55]. Building on these perspectives, the seventh hypothesis is proposed as follows:

Hypothesis H7a: Organizational culture has a positive effect on perceived usefulness.

Hypothesis H7b: Organizational culture has a positive effect on the intention to adopt AI in manufacturing enterprises in the Southeast region of Vietnam.

(vi) Perceived Usefulness (PU)

Technology acceptance is largely influenced by users' perceptions of the benefits associated with adopting a specific technological solution. When individuals or organizations anticipate favorable outcomes from utilizing a given technology, they are more inclined to form intentions to adopt and use it by Dai, et al. [33]; Kim and Song [56]. In the context of Industry 4.0, perceived usefulness (PU) reflects users' beliefs that implementing components such as the Internet of Things (IoT), Cloud Computing, Augmented Reality (AR), Virtual Reality (VR), Artificial Intelligence (AI), and Robotics can improve work efficiency and productivity by Aceto, et al. [57]; Shrivastava, et al. [58]; Cordero, et al. [59]. Research has further demonstrated a positive relationship between PU and both business readiness by Chidambaram and Nagarajan [60] and the digital transformation of small and medium-sized enterprises by Franco, et al. [61]. Nonetheless, current literature on PU is somewhat limited in scope, restricting its capacity to offer comprehensive insights for policymakers, scholars, and industry professionals.

Notably, a recent study found that PU significantly fosters a positive attitude toward Industry 4.0 adoption by Cordero, et al. [59]. According to Ajzen [62] users' intention to adopt technology is shaped by their perceptions of its usefulness. This research employs the Technology Acceptance Model (TAM), which posits a direct relationship between perceived usefulness and the intention to adopt technology by Maartje, et al. [63]. TAM also integrates factors such as subjective norms, social image, job relevance, output quality, and result demonstrability by Venkatesh and Bala [64]. These elements suggest that users evaluate PU through cognitive comparisons between the system's capabilities and the demands of their job roles by Venkatesh and Davis [22]. Accordingly, it is posited that perceived usefulness positively influences individuals' intentions to embrace new technological innovations. Based on these considerations, the eighth hypothesis is formulated as follows:

Hypothesis H8: Perceived usefulness has a positive impact on the intention to adopt AI in manufacturing enterprises in the Southeast region of Vietnam.

3.2. Research Model

Based on the literature review of the current research status, relevant theories, and the specific characteristics of manufacturing enterprises in the Southeast region, the author proposes the following model (Figure 1).

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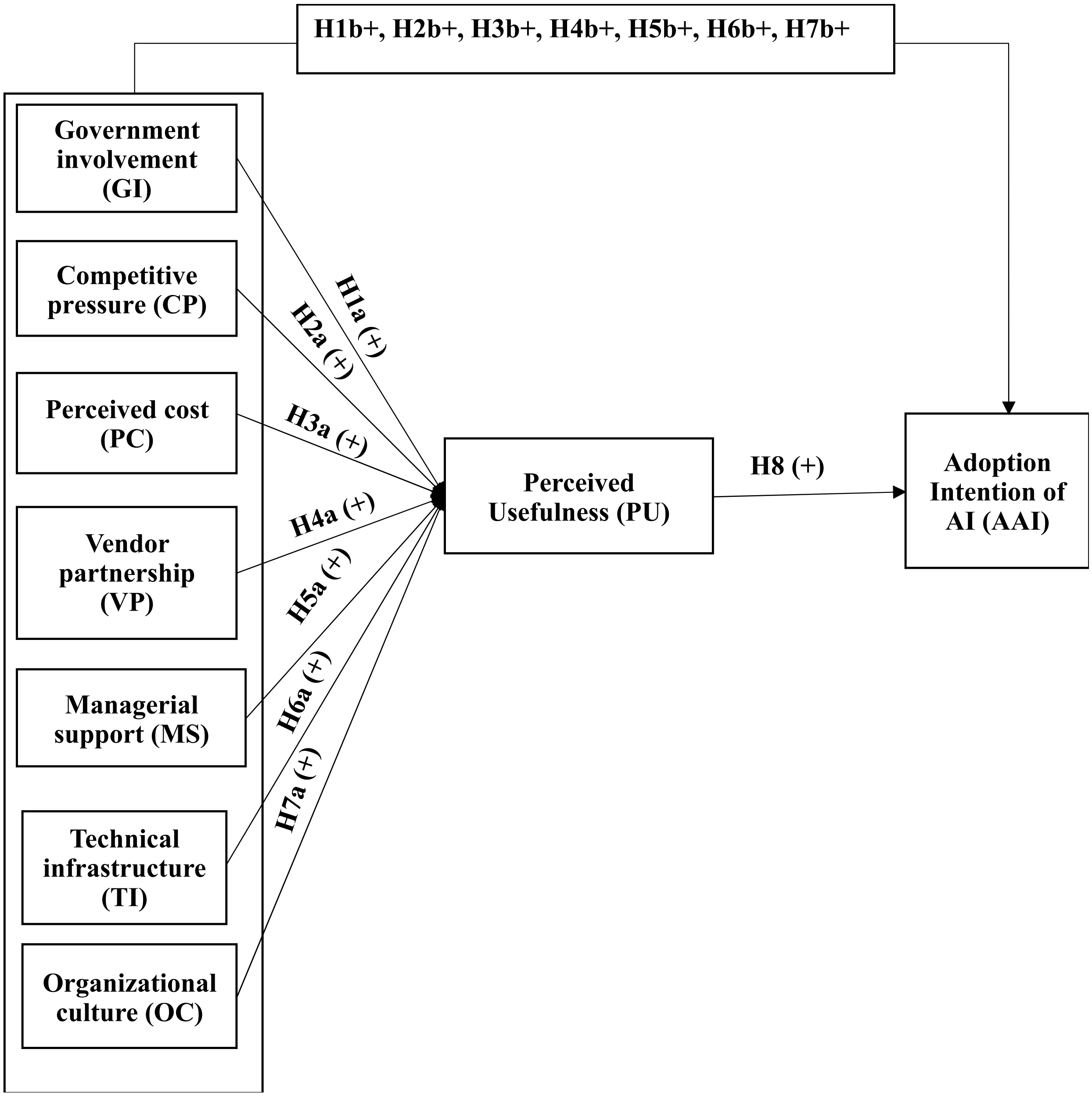

Figure 1.
Research model

4. Research Methodology

4.1. Qualitative and Quantitative Research Methods

4.1.1. Qualitative Research Methods

The author conducted a focus group discussion with three experts and another group discussion involving seven heads or deputy heads of departments responsible for various functions within manufacturing enterprises in the Southeast region of Vietnam. The purpose was to explore factors influencing perceived usefulness and the adoption intention of artificial intelligence (AI), as well as to refine the measurement scales of the constructs in the research model to better fit the practical research context. Subsequently, a quantitative survey was carried out with leaders of manufacturing enterprises in the Southeast region to collect empirical data.

4.1.2. Quantitative Research Methods

The collected data were processed using SPSS 29.0 and AMOS 29.0. A preliminary study was conducted by distributing survey questionnaires to 110 managers of manufacturing enterprises in the Southeast region of Vietnam. Reliability and factor-loading assessments were performed. The proposed measurement system in the research model was fully accepted, with none of the 34 observed variables across the 8 measurement scales being eliminated, indicating that all research indicators met the required criteria. Subsequently, the author conducted a formal quantitative study using 435 valid responses. The data were coded and analyzed through a series of statistical procedures, including Exploratory Factor Analysis (EFA), Confirmatory Factor Analysis (CFA), and Structural Equation Modeling (SEM).

4.2. Survey Form

According to Hair, et al. [65] conduct an exploratory factor analysis (EFA), the recommended sample size should follow a ratio of at least 10 observations per measured variable. Given that the proposed research model includes a total of 38 observed variables (as listed in Appendix 1), the minimum required sample size is 10 × 38 = 380 observations. To enhance the reliability of the study, the author aimed to survey 435 manufacturing enterprises in the Southeast region. A convenience sampling method was employed, targeting senior management personnel from 435 manufacturing firms in the Southeast region who had expressed an intention to adopt artificial intelligence (AI) within their organizations. Each firm was represented by a single respondent, providing one completed questionnaire per enterprise. After screening, all 435 collected responses were deemed valid and were used for formal analysis to evaluate the factors influencing perceived usefulness and the intention to adopt AI in manufacturing enterprises in the Southeast region.

4.3. Build a Scale

The study employed a five-point Likert scale to measure the factors influencing perceived usefulness and the intention to adopt artificial intelligence in manufacturing enterprises in the Southeast region of Vietnam. The scale ranged from (1) Strongly Disagree, (2) Disagree, (3) Neutral, (4) Agree, to (5) Strongly Agree.

5. Research Results

5.1. Descriptive Statistics of the Survey Sample

The study collected data from 435 manufacturing enterprises (Mes) in the Southeast region of Vietnam. A total of 435 valid responses were obtained, with general information summarized as follows:

Table 1.
Survey sample characteristics.

Character		Frequency	Percent (%)
Type of enterprise	Foreign Direct Investment (FDI) Enterprise	4	0.9
	Domestic Private Enterprise (without foreign investment)	430	98.9
	State-owned Enterprise (SOE)	1	0.2
	Total	435	100,0
Business activities	Consumer Goods	3	0.7
	Processing Technology	25	5.7
	Furniture	21	4.8
	Mechanical Engineering, Machinery Manufacturing, Furniture, Consumer Goods	1	0.2
	Mechanical Engineering, Machinery Manufacturing, Consumer Goods, Processing Industry	1	0.2
	Electronics	71	16.3
	Mechanical Engineering, Machinery Manufacturing	30	6.9
	Other Business Activities	283	65.1
	Total	435	100.0
Number of employees in the enterprise (unit: persons)	<50	86	19.8
	50 – 100	133	30.6
	101 – 200	124	28.5
	201 – 500	61	14.0
	>500	31	7.1
	Total	435	100.0

Table 1 presents the demographic characteristics of the 435 valid responses collected from manufacturing enterprises (Mes) in the Southeast region of Vietnam. Regarding enterprise type, 4 were foreign direct investment (FDI) enterprises, accounting for 0.9%; 430 were domestic private enterprises (without foreign investment), accounting for 98.9%; and 1 was a state-owned enterprise, accounting for 0.2%. In terms of industry sector, 3 enterprises were engaged in consumer goods manufacturing (0.7%); 25 in processing industries (5.7%); 21 in furniture manufacturing (4.8%); 1 enterprise operated across mechanical engineering, machinery manufacturing, furniture, electronics, and consumer goods (0.2%); and 1 enterprise specialized in mechanical engineering, machinery manufacturing, consumer goods, and processing industries (0.2%). There were 71 enterprises in electronics manufacturing (16.3%); 30 in mechanical engineering and machinery manufacturing (6.9%); and 283 enterprises in other industries (65.1%). Regarding enterprise size by number of employees, 86 enterprises employed fewer than 50 people (19.8%); 133 had between 50 and 100 employees (30.6%); 124 had between 101 and 200 employees (28.5%); 61 had between 201 and 500 employees (14.0%); and 31 enterprises employed more than 500 people (7.1%).

5.2. Evaluate the Reliability of the Scale

Table 2 presents the reliability assessment results, showing that all measurement scales achieved Cronbach's Alpha coefficients ranging from 0.800 to 0.890. All observed variables within the scales had item-total correlation coefficients greater than 0.3, demonstrating that the measurement scales used in this study possess high internal consistency. These results confirm that the scales meet the reliability requirements and are therefore retained for subsequent analyses, including Exploratory Factor Analysis (EFA).

Table 2.
Results of reliability assessment.

Variables	Cronbach's Alpha	Corrected Item-Total Correlation
Government involvement (GI)	0.890	0.688 – 0.739
Competitive pressure (CP)	0.842	0.624 – 0.668
Perceived cost (PC)	0.814	0.650 – 0.674
Vendor partnership (VP)	0.839	0.661 - 0.693
Managerial support (MS)	0.847	0.644 - 0.670
Technical infrastructure (TI)	0.800	0.618 - 0.662
Organizational culture (OC)	0.830	0.623 - 0.672
Perceived usefulness (PU)	0.862	0.680 – 0.722
Adoption Intention of AI (AAI)	0.823	0.639 – 0.660

5.3. Exploratory Factor Analysis (EFA)

Table 3 presents the results of the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's Test of Sphericity, indicating that the data are highly suitable for factor analysis. Specifically, the KMO value reached 0.953, exceeding the minimum threshold of 0.6. This value demonstrates strong sampling adequacy, ensuring that the observed variables are sufficiently correlated to proceed with Exploratory Factor Analysis (EFA).

Moreover, Bartlett's Test yielded a Chi-Square value of 8453.187 with 703 degrees of freedom (df) and a significance level (Sig.) of 0.000. Since Sig. < 0.05, the null hypothesis—that the correlation matrix is an identity matrix—can be rejected. This indicates that the observed variables in the model have significant correlations, making factor analysis appropriate. These results also confirm the strong interrelationships among the variables, supporting the validity of conducting factor analysis in this study.

Table 3.
KMO and Bartlett's Test Results.

Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy		0.953
Bartlett's Test of Sphericity	Approximate Chi-Square Value	8453.187
	Degrees of Freedom	703
	Significance Level	0.000

5.4. Confirmatory Factor Analysis (CFA)

The results of the CFA analysis in table 4 indicate that all model fit indices meet the necessary criteria, reinforcing the validity of the model in this study. Specifically, the CMIN/df value is 1.107, which is below the threshold of 5, indicating a good model fit without excessive complexity. The GFI is 0.925, exceeding the ideal cutoff of 0.9, suggesting a good fit. The TLI and CFI values are 0.991 and 0.992, respectively, both surpassing the minimum threshold of 0.9, demonstrating excellent model fit. The RMSEA is 0.016, well below the cutoff of 0.08, further confirming the very high fit of the Confirmatory Factor Analysis (CFA) model. These indices collectively demonstrate that the model fits the research data well, ensuring the reliability of the CFA results. Key fit indices such as CMIN/df, GFI, TLI, CFI, and RMSEA all meet the standard thresholds, confirming that the model exhibits excellent fit and can be confidently used for further analysis in this study.

Table 4.
Fit Indices for Confirmatory Factor Analysis (CFA).

Indicator	CMIN/df	GFI	TLI	CFI	RMSEA
Value	1.107	0.925	0.991	0.992	0.016
Benchmark Value	< 5	> 0.9	> 0.9	> 0.9	< 0.08
Conclusion	Satisfied	Satisfied	Satisfied	Satisfied	Satisfied

5.5. Structural Equation Modeling (SEM) Analysis
5.5.1. Assessment of SEM Model Fit

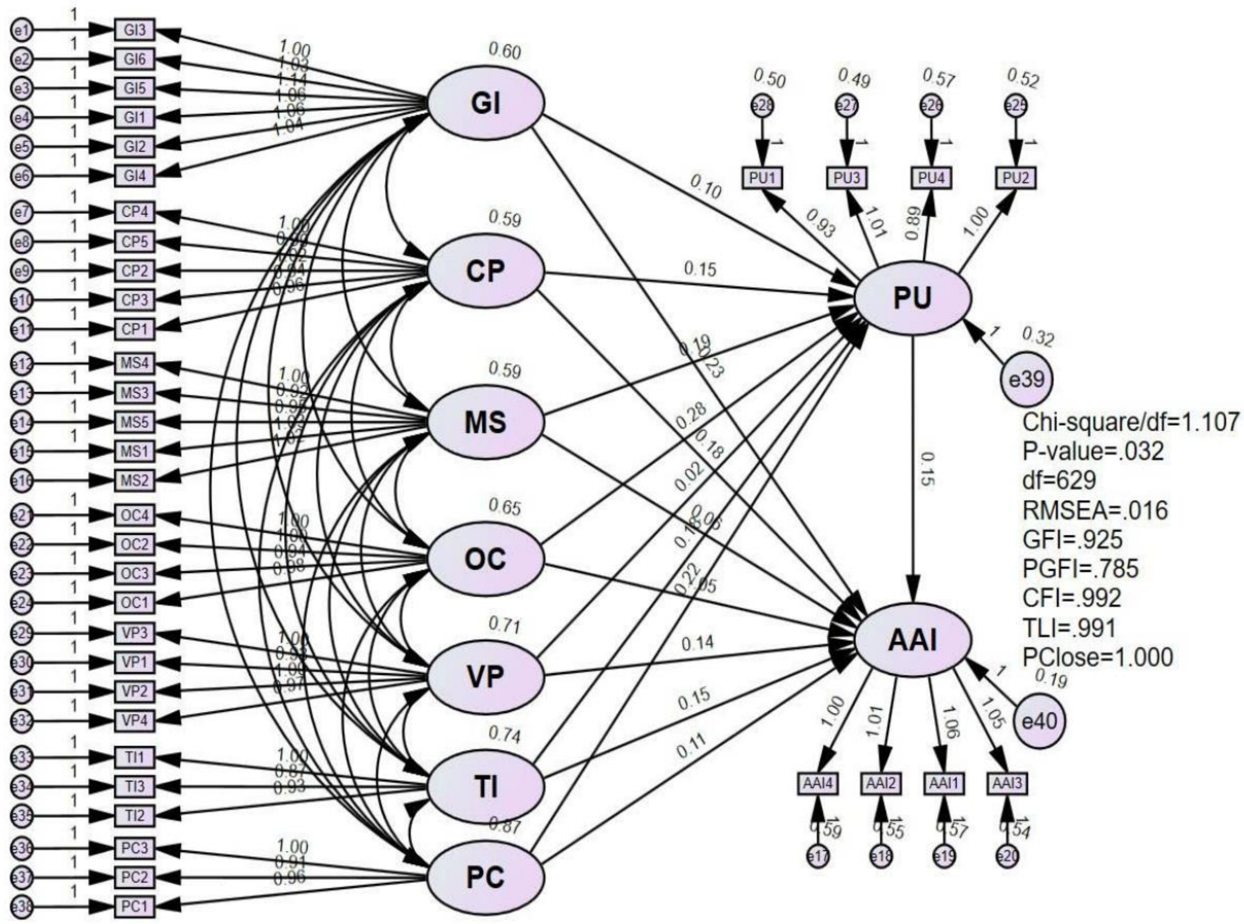

Figure 2.
Results of the SEM Model Analysis.

The results of the Structural Equation Modeling (SEM) analysis, as presented in the figure 2, indicate that the model exhibits a good fit with the collected data. All model fit indices meet the required standards, reinforcing the model's validity in this study. Specifically, the Chi-square/df ratio is 1.107, which is below the threshold of 5, indicating a good fit without excessive complexity. Other fit indices, including RMSEA = 0.016 (below the 0.08 threshold), GFI = 0.925, CFI = 0.992, and TLI = 0.991, all reach excellent values, surpassing the minimum acceptable criteria (GFI > 0.9, CFI and TLI > 0.9, RMSEA < 0.08). The Pclose value of 1.000 further confirms a perfect fit between the model and the data. Regarding the relationships within the model, most path coefficients between latent constructs and observed variables are statistically significant, demonstrating strong associations among the factors.

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5.5.2. Hypothesis Testing

Table 5.
Bootstrap Test Results of Direct Relationships in the Research Model.

Research hypothesis	Relationship	Standardized Path Coefficient	Significance Level in SEM Analysis	Bootstrap Significance Level (Bias-Corrected Method)	Conclusion
H1a	GI → PU	0.229	***	0.005	Supported
H1b	GI → AAI	0.079	0.181	0.334	Not supported
H2a	CP → PU	0.125	0.033	0.103	Not supported
H2b	CP → AAI	0.171	0.004	0.031	Supported
H3a	PC → PU	0.218	0.002	0.023	Supported
H3b	PC → AAI	0.131	0.078	0.162	Not supported
H4a	VP → PU	0.022	0.707	0.764	Not supported
H4b	VP → AAI	0.150	0.012	0.048	Supported
H5a	MS → PU	0.157	0.005	0.024	Supported
H5b	MS → AAI	0.058	0.306	0.437	Not supported
H6a	TI → PU	0.163	0.012	0.033	Supported
H6b	TI → AAI	0.161	0.016	0.059	Not supported
H7a	OC → PU	0.240	***	0.002	Supported
H7b	OC → AAI	-0.055	0.385	0.523	Not supported
H8	PU → AAI	0.183	0.014	0.035	Supported

With a 95% confidence level, the bootstrap test results in Table 5 indicate that, except for seven hypotheses that were rejected—namely H1b, H2a, H3b, H4a, H5b, H6b, and H7b—all other hypotheses were accepted. This implies that government involvement, perceived cost, management support, technical infrastructure, and organizational culture positively impact perceived usefulness. Meanwhile, competitive pressure and supplier partnerships directly influence the intention to adopt artificial intelligence. Additionally, perceived usefulness plays a strong mediating role in affecting the intention to adopt AI.

5.5.3. Evaluating the Mediating Role of Perceived Usefulness (PU)

Table 6.
Results of the Mediation Analysis for PU.

Relationship	Direct Standardized Effect (excluding PU)	P-value (BC)	Indirect Standardized Effect (via PU)	P-value (BC)	Conclusion
PC → PU → AAI	0.131	0.162	0.040	0.036	Full mediation
TI → PU → AAI	0.161	0.059	0.030	0.036	Full mediation
VP → PU → AAI	0.150	0.048	0.004	0.621	No mediation role
OC → PU → AAI	-0.055	0.523	0.044	0.020	Full mediation
MS → PU → AAI	0.058	0.437	0.029	0.028	Full mediation
CP → PU → AAI	0.171	0.031	0.023	0.062	No mediation role
GI → PU → AAI	0.229	0.005	0.015	0.224	No mediation role

Based on the analysis results in Table 6, Perceived Usefulness (PU) plays a full mediating role in the relationships between Perceived Cost (PC) → PU → AI Adoption Intention (AAI), Technical

Infrastructure (TI) → PU → AAI, Organizational Culture (OC) → PU → AAI, and Managerial Support (MS) → PU → AAI. This is evidenced by the statistically significant indirect effects through PU, while the direct effects are either insignificant or very weak.

However, PU does not act as a mediator in the relationships between Vendor Partnership (VP) → PU → AAI, Competitive Pressure (CP) → PU → AAI, and Government Involvement (GI) → PU → AAI, as the indirect effects through PU are not statistically significant, despite the presence of direct effects on AAI.

6. Discussions

The results of the quantitative study, employing Structural Equation Modeling (SEM), indicate a high level of model fit with the survey data. Goodness-of-fit indices such as Chi-square/df, GFI, CFI, TLI, and RMSEA all fall within ideal thresholds, with a particularly favorable RMSEA value of 0.016, signifying an excellent model-data fit.

Regarding hypothesis testing, the findings confirm several associations consistent with prior studies. Specifically, Government Involvement (GI) was found to have a positive effect on Perceived Usefulness (PU), aligning with the findings of Hsu, et al. [48] and Ghani, et al. [13] emphasized the crucial role of governmental support in creating an enabling environment for AI adoption. However, GI did not exhibit a significant direct effect on the Actual AI Adoption Intention (AAI), reflecting a gap between long-term perceived benefits and immediate adoption behavior. This is consistent with the findings of Kwak, et al. [14] who suggested that government involvement primarily exerts an indirect influence by fostering a supportive environment rather than directly driving adoption.

Competitive Pressure (CP) was found to have a significant and direct positive influence on AAI. This supports the conclusions of Kwak, et al. [14] and Le Tan, et al. [7] who argued that competitive market pressures serve as a strong impetus for firms to innovate and adopt advanced technologies in order to maintain a sustainable competitive advantage.

Meanwhile, Perceived Cost (PC) had a significant positive effect on PU, but no direct impact on AAI. This result aligns with the findings of Abaddi [9] who suggested that perceived cost acts as a barrier that must be overcome before a firm commits to the adoption of new technologies.

The study further affirms the positive role of Managerial Support (MS) in enhancing PU. This finding is supported by Chatterjee, et al. [11]; Ghani, et al. [13] and Hsu, et al. [48] all emphasized the importance of top management commitment in fostering employee awareness and engagement in technological adoption.

Technical Infrastructure (TI) also emerged as a significant determinant of PU. This is consistent with the findings of Chuyen, et al. [15] who argued that a well-established information technology infrastructure greatly facilitates the perception of AI's usefulness in manufacturing operations.

Notably, Organizational Culture (OC) was found to have a strong and positive effect on PU. This finding reinforces the insights from Usman, et al. [55] who highlighted that organizations fostering open, innovative, and supportive cultures are more likely to perceive the benefits of AI and thereby increase their likelihood of adoption.

As for the mediating role, PU had a clear and significant positive impact on AAI, reinforcing the Technology Acceptance Model (TAM) proposed by Davis [21]. This result is also in agreement with Chatterjee, et al. [11] who asserted that PU is the most influential factor determining AI adoption behavior.

Interestingly, Vendor Partnership (VP), despite being emphasized in previous studies (e.g., [42, 48]) did not significantly influence PU in this study. However, it had a direct positive impact on AAI, opening new discussions on vendor relationships' distinct role within the Southeastern region's manufacturing context.

Overall, the comparison with prior studies confirms the validity and reliability of the current research findings. Simultaneously, the study provides novel insights by clarifying the influence and magnitude of various determinants under real-world conditions in the manufacturing sector of the Southeastern region.

Moreover, when integrated with the qualitative findings, these results underscore the practical factors affecting perceptions and behaviors toward AI adoption, offering critical managerial implications. Specifically, manufacturing firms should focus on cultivating an innovation-oriented organizational culture, developing robust technical infrastructure, and proactively leveraging governmental support policies to enhance readiness and effectiveness in future AI implementation.

7. Conclusions and Implications

7.1. Conclusions

The research findings indicate that key factors—including Government Involvement (GI), Competitive Pressure (CP), Perceived Cost (PC), Vendor Partnership (VP), Managerial Support (MS), Technological Infrastructure (TI), and Organizational Culture (OC)—influence both Perceived Usefulness (PU) and the Adoption Intention of AI (AAI). Among these, Competitive Pressure and Vendor Partnership exert a significant direct impact on the intention to adopt AI. Furthermore, the pivotal role of Perceived Usefulness (PU) is confirmed through its strong direct effect on AI adoption intention, thereby reinforcing the relevance and applicability of the Technology Acceptance Model (TAM) in examining the technology adoption behavior of manufacturing enterprises.

7.2. Implications

Firstly, the study confirms the pivotal role of the government in promoting AI adoption among enterprises in the Southeastern region of Vietnam. Firms should take advantage of supportive policies, public-private partnership programs, and government-led pilot projects by maintaining positive relationships with regulatory bodies, participating in conferences, and engaging in regular information exchanges. Establishing a policy monitoring unit is essential to proactively identify suitable opportunities, prepare necessary resources, and develop feasible proposals. These actions allow firms to optimize policy benefits, enhance competitiveness, and accelerate the application of AI.

Secondly, competitive pressure acts as a major driver for AI adoption. Enterprises are encouraged to monitor competitors' technological strategies, form specialized teams to analyze AI trends in their respective industries and develop early warning systems to enable timely decision-making. Internal strategic discussions should also be conducted to assess organizational strengths and weaknesses and to formulate appropriate AI strategies to sustain long-term competitive advantage.

Thirdly, perceived cost significantly influences decisions regarding AI investment. Firms should carefully evaluate long-term cost–benefit implications and clearly communicate the strategic value of AI to stakeholders. Choosing reputable AI vendors that align with the firm's financial capabilities is critical to ensure effective investment and foster internal consensus during implementation.

Fourthly, strategic partnerships with AI vendors facilitate access to advanced technologies, technical support, and tailored consultancy. Such relationships enhance the perceived usefulness of AI and reduce the associated investment risks. Enterprises should select trustworthy partners with proven implementation capabilities and cultivate long-term relationships based on mutual trust and shared objectives to maximize the benefits of AI applications.

Fifthly, top management support is a decisive factor in AI deployment. Leadership should demonstrate a clear commitment through strategic planning, appropriate resource allocation, capacity-building efforts, and incentive policies that promote innovation. These efforts help establish a conducive environment for successful technological transformation.

Sixthly, a modern technical infrastructure serves as the foundation for effective AI applications. Enterprises must invest in advanced hardware, software, high-speed networking systems, and cybersecurity solutions. This infrastructure enhances the ability to implement AI and improves productivity and competitiveness.

Seventhly, an innovation oriented organizational culture encourages AI adoption. Management should convey a clear vision for innovation, foster a supportive environment for experimentation, recognize employee initiatives, establish innovation forums, and support the piloting of new solutions. These practices help build a sustainable foundation for the long-term integration of AI technologies.

Eighthly, awareness of AI's benefits plays a critical role in shaping adoption intentions. Firms should offer training sessions, conduct experience-sharing workshops, maintain frequent internal communications, and showcase successful case studies. Additionally, evaluating the effectiveness of awareness initiatives allows organizations to fine tune strategies and optimize AI implementation outcomes.

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The authors confirm that the manuscript is an honest, accurate and transparent account of the study that no vital features of the study have been omitted and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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