DETERMINANTS OF ARTIFICIAL INTELLIGENCE ADOPTION IN MALAYSIA'S PUBLICLY LISTED MANUFACTURING SECTOR

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ABSTRACT

Artificial intelligence (AI) has the potential to transform organizational performance; however, AI adoption among Malaysian publicly listed manufacturing companies (PLMCs) remains relatively low and uneven. Key challenges include limited technological readiness, insufficient organizational support, and unclear external pressures influencing adoption decisions. Therefore, this study aims to (1) examine the current level of AI adoption, (2) determine the relationships between Technology–Organization–Environment (TOE) determinants and AI adoption, and (3) assess the impact of these determinants on AI adoption among PLMCs in Malaysia. A quantitative research design using a descriptive correlational approach was employed. The respondents comprised 126 top management members, managers, and supervisors representing PMLCs. Simple random sampling was used to select the sample. Data were collected through a structured self-administered online questionnaire using a 7-point Likert scale. Statistical analyses, including descriptive statistics, correlation analysis, and multiple regression analysis, were conducted using SPSS. The results indicate that AI adoption among Malaysian PLMCs is still at an early stage, with most firms planning or partially implementing AI. Correlation analysis revealed that all TOE determinants significantly relate to AI adoption, although the relationships were weak to moderate. Regression analysis showed that competitive pressure is the only determinant that significantly influences AI adoption, while technological and organizational factors play supportive roles. The findings provide important theoretical and practical implications by highlighting the dominant role of environmental forces in driving AI adoption. The study contributes to the TOE literature and offers insights for managers and policymakers to design strategies and policies that promote sustainable AI adoption in the manufacturing sector.

Keywords: *Artificial Intelligence (AI) Adoption, Technology–Organization–Environment (TOE) Determinants, Manufacturing Companies, Publicly Listed Companies*

1. INTRODUCTION

The manufacturing sector contributes approximately 22% to 24% of Malaysia's Gross Domestic Product (GDP), as reported by the Department of Statistics Malaysia [1]. Therefore, it serves as the key driver of industrialization, employment, and export earnings. Major industries include electronics and electrical, automotive, palm oil-based products, rubber and gloves, and machinery. The sector plays a vital role in generating foreign exchange, attracting foreign direct investment (FDI), and facilitating Malaysia's integration into global supply chains. In 2023, manufacturing companies contributed around 85% of Malaysia's total exports [2] and attracted around 45% of Malaysia's total FDI [3].

In Bursa Malaysia Main Market (or Main Board), the publicly listed manufacturing companies (PLMCs) are categorized under the Industrial Product & Services sector, as Publicly Listed Companies (PLCs) in this sector are involved in machinery and automation. According to the latest quarterly review issued in March 2025, the Industrial

& Service sector was at the level of RM201.48 billion market capitalization, which contributed to 11% of the total Main Market capitalization in Bursa Malaysia [4]. Among the 13 market sectors in the Main Market, the Industrial Products & Services sector contributes significantly to overall market capitalization. In other words, the performance of PLMCs plays a vital role in the well-being of the manufacturing industry, specifically, and the economy of the country in general.

According to recent global assessments, investments in industrial digitalization have surged significantly since 2020, with annual figures exceeding USD 900 billion, reflecting the strategic prioritization of digital transformation among enterprises worldwide [5]. Contemporary literature emphasizes that successful digitalization under the Industry 4.0 paradigm requires not only technological upgrades but also environmental and social adaptability to ensure sustainable growth and organizational innovation [6]. In response to these changes, many governments have developed national strategies to accelerate AI adoption. The National Policy on Industry 4.0 (Industry4WRD), launched by the Ministry of International Trade and Industry in 2018, aims to transform Malaysian industries into smart manufacturing ecosystems through the integration of advanced technologies, including AI. The National Fourth Industrial Revolution (4IR) Policy identifies AI as a key technology that is foundational to the nation's 4IR agenda and stresses the need to develop ethical use of AI for transforming the economy. This policy highlights the critical need for Malaysian firms to innovate and adopt disruptive technologies to drive productivity, sustainability, and global relevance [7].

Despite these national initiatives, recent reports indicate that Malaysia's integration of AI remains in its early stages, with only 15% to 20% of companies actively adopting Industry 4.0 technologies [8]. Manufacturing firms face several barriers and challenges in implementing AI, largely due to the nascent stage of AI adoption in the country. These challenges include a shortage of skilled talent, limited incentives, and a lack of innovation [9]. The slow uptake of AI in this critical sector raises concerns about Malaysia's competitiveness in the global manufacturing landscape and highlights the need for a deeper understanding of the underlying issues.

One of the main challenges in the Malaysian context is the gap between policy support and actual organizational capability. While government support exists in the form of grants, incentives, and strategic roadmaps, many firms lack the internal technological infrastructure and leadership commitment to capitalize on these opportunities. For instance, 57% of Malaysian small and medium-sized enterprises (SMEs) are not yet prepared for digital transformation in their daily operation [10], showing a lack of substantial interest in AI adoption among these businesses in Malaysia. This indicates that companies in Malaysia still rely on traditional methods to run their business. Determinants such as limited Information Technology (IT) capability, unclear digital strategies, and inadequate support from top management have been identified as key barriers [11]. However, there is limited empirical evidence that evaluates how these determinants interact within the unique socio-economic and regulatory environment of Malaysia.

While there are existing studies to discuss the determinants influencing technology adoption in several frameworks, such as the Technology Acceptance Model [12] and the Unified Theory of Acceptance and Use of Technology [13], most of these studies on AI adoption are either conceptual or based on data from more developed countries, making them less applicable to the Malaysian context. Therefore, it is a pressing need to identify the specific determinants that influence AI adoption in Malaysian manufacturing firms. Without a clear understanding of these determinants, efforts to accelerate AI integration may fail to address the real challenges faced by local industries.

This study, therefore, seeks to bridge this gap by empirically examining the technological, organizational, and environmental determinants that influence AI adoption, using the TOE framework as a guiding model [14]. Addressing this gap by understanding the determinants that influence AI adoption in the Malaysian context can provide valuable insights for the development of strategies to promote technology adoption and innovation, in order to remain competitive and relevant in this digital era.

Despite the increasing importance of AI in manufacturing, empirical evidence on the determinants influencing AI adoption among publicly listed manufacturing companies (PLMCs) in Malaysia remains limited. Existing studies have primarily focused on SMEs, conceptual discussions, or evidence from developed economies, resulting in limited contextual understanding of AI adoption within Malaysia's publicly listed manufacturing sector. Therefore, this study seeks to address this

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research gap by examining AI adoption through the TOE framework.

Based on the issues discussed above, three (3) research questions to be addressed in this study are:

i. What is the current state of the AI adoption level among PLMCs in Malaysia?

ii. What is the relationship between TOE determinants and AI adoption among PLMCs in Malaysia?

iii. What are the impacts of the TOE determinants on the AI adoption among PLMCs in Malaysia?

2. LITERATURE REVIEW

2.1 AI Adoption in the Manufacturing Sector

In particular, the adoption of AI technologies has been widely recognized for its ability to enhance decision-making, streamline operations, and drive overall productivity within manufacturing and service sectors [15, 16]. In the manufacturing sector, AI technologies have been increasingly adopted to optimize production lines, reduce downtime through predictive maintenance, ensure quality control, and enhance supply chain efficiency [15]. Thus, adopting AI can benefit companies by promoting corporate success, leading to cost efficiency and business value [15, 16].

Despite these advantages, many organizations, especially in developing economies, continue to face significant barriers to AI adoption, including infrastructure limitations, skill gaps, and organizational resistance [6]. Similarly, Malaysia is not exempt from such a dilemma. Even with the 4IR policy efforts, the AI adoption rate in Malaysian businesses remains limited because such adoption deals with more complicated data and requires deep learning and understanding. Malaysia has shown a slow uptake of 4IR in 2022, where only 15% to 20% of businesses have fully embraced 4IR [17]. This slow adoption is concerning, especially as Malaysia seeks to position itself as a digital transformation leader in the ASEAN region [7]. Several barriers, such as low technological readiness, lack of strategic Information Technology (IT) capability, minimal leadership engagement, and limited clarity on government support, continue to hinder wider AI implementation.

2.2 Related Work on AI Adoption

The adoption of AI has become an increasingly important research area due to its potential to improve operational efficiency, decision-making capabilities, and organizational competitiveness. To explain organizational technology adoption, researchers have employed various theoretical frameworks, including the Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT), and the Technology–Organization–Environment (TOE) framework. Among these approaches, the TOE framework has gained considerable attention because it provides a comprehensive perspective by examining technological, organizational, and environmental factors simultaneously.

Several studies have applied the TOE framework to investigate AI adoption across different organizational contexts. Ghani et al. [14] found that technological readiness, organizational support, and environmental conditions significantly influenced AI adoption among manufacturing companies. Similarly, Badghish and Soomro [18] reported that technological capability and organizational readiness were important determinants of AI adoption among small and medium-sized enterprises (SMEs). Other studies, such as Suddin et al. [19] and Lim and Seng [20], emphasized the roles of top management support, financial readiness, and government support in facilitating AI implementation. These studies collectively suggest that successful AI adoption depends on the interaction of internal organizational capabilities and external environmental influences.

Despite these contributions, several limitations remain in the existing literature. First, most studies have focused on SMEs, service industries, or organizations operating in developed economies. Consequently, empirical evidence regarding AI adoption among publicly listed manufacturing companies remains limited, particularly in emerging economies such as Malaysia. Second, previous studies have reported inconsistent findings concerning the relative importance of TOE determinants. While some researchers identified technological readiness as the dominant factor, others emphasized organizational capabilities or environmental pressures. These inconsistencies indicate that the influence of TOE determinants may vary according to industrial context, organizational characteristics, and economic environment.

Furthermore, many existing studies primarily examine the direct relationships between TOE determinants and AI adoption without adequately comparing the relative influence of these factors when analyzed simultaneously. As a result, there is limited understanding of which determinants exert the strongest impact on AI adoption decisions in highly competitive manufacturing environments. This limitation restricts the ability of managers and policymakers to prioritize resources and formulate effective strategies for AI implementation.

2.3 Theoretical Framework

The TOE framework is a theoretical model that can be used to study the adoption and implementation of new technologies within organizations [14], which will help businesses to understand the determinants that influence technological innovation by examining how these three key elements combine to affect the organization's decision on which technologies to employ. Hence, organizations can be better informed of their decisions surrounding AI adoption.

The TOE framework, originally introduced by Tornatzky and Fleischer [21], remains a widely used theoretical model for examining technology adoption at the organizational level. The framework outlines three key contextual dimensions - technological, organizational, and environmental - that collectively influence an organization's decision to adopt and implement new technologies [22]. The technological context refers to the characteristics and availability of relevant technologies; the organizational context includes factors such as firm size, resources, and structure; and the environmental context involves external elements like industry trends, competition, and regulatory pressures [23]. These three dimensions provide a comprehensive lens for understanding how firms evaluate, respond to, and integrate technological innovations into their operations [24].

2.4 Determinants that influence AI adoption

From the TOE framework perspective, this research looks at how the determinants in these three (3) key aspects - technological infrastructure, internal organization dynamics, and external environment – interact to affect the organization's decisions for AI adoption in the Malaysian manufacturing context, especially those listed on Bursa Malaysia Main Market. As identified by previous studies, such determinants can be IT capacity, complexity, top management support, financial readiness, government support, and competitive pressure. The six determinants - IT capability, complexity, top management support, financial readiness, government support, and competitive pressure - were selected based on their alignment with the TOE framework, ensuring comprehensive coverage of technological, organizational, and environmental determinants influencing AI adoption. These determinants are consistently supported by empirical studies and are highly relevant to the Malaysian manufacturing context, where issues such as limited IT infrastructure, leadership commitment, and regulatory support significantly impact adoption. Their selection also addresses a research gap in understanding AI adoption among publicly listed manufacturing companies in Malaysia, offering practical insights for both industry stakeholders and policymakers.

2.4.1 Technological Aspect

2.3.1.1 IT Capability

IT capability refers to an organization's ability to leverage and integrate IT resources to drive business processes and innovations. In the context of AI adoption, this involves the technical infrastructure, the skill set of employees, and the alignment of IT systems with organizational goals [25]. Previous reports also highlighted that manufacturing firms with strong IT infrastructure and skilled personnel are better positioned to harness the potential of innovative technology [26]. A study in SME has shown that the important role of IT compatibility in driving the companies to adopt AI [18].

Therefore, a robust IT capability provides the foundation for integrating advanced technologies into manufacturing processes, especially when AI-like technology involves software to automate processes and procedures to improve the efficiency and effectiveness in managing the manufacturing data. For example, the business software – Material Requirements Planning (MRP), is one of the popular IT tools employed by many manufacturers for their production planning. Manufacturers used MRP to optimize their operations by forecasting demand, scheduling production, and managing material procurement. Nevertheless, MRP vendors today are taking advantage of new technology to improve their products and offer more capabilities, with the

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integration of machine learning and AI in advanced planning processes. Hence, the company requires more technological capability in order to adopt rapid technology transformation toward a smart manufacturing environment. According to those statements, hypothesis H1 is:
H1: IT capability has a significant positive relationship with AI adoption among PLMCs in Malaysia.

2.3.1.2 Complexity

Complexity reflects the level of difficulty associated with the adoption of new technology. The sophistication of AI systems can present significant adoption challenges and often requires specialized infrastructure and integration with existing IT systems [18, 27]. While PLCs typically possess greater resources, they still face substantial hurdles in deploying advanced AI solutions. PLCs often require specialized technical expertise to properly implement and integrate these complex systems across their operations, which resulted in workforce restructuring: Companies must balance human-AI collaboration models [27]. Particularly in the case of manufacturers, these firms face scale-related challenges when deploying AI across global production networks, despite having greater financial resources.

This necessitates strategic investments in several key areas: developing in-house AI capabilities, building appropriate technological infrastructure, and potentially engaging third-party experts through consulting arrangements or strategic partnership [16]. The implementation complexity is further compounded by the need to align AI initiatives with shareholder expectations and financial reporting requirements as for PLCs. According to those statements, hypothesis H2 is:
H2: Complexity has a significant negative relationship with AI adoption among PLMCs in Malaysia.

2.4.2 Organizational Aspect

2.3.2.1 Top Management Support

Another group of studies has shown a positive relationship between top management support and AI adoption. Top management support is vital in setting strategic priorities, allocating resources, and fostering a culture of innovation [15]. Research suggests that strategically investing in top management commitment can increase the chance of successful adoption of AI technologies [19]. Therefore, the top management should realize the business-oriented benefits of AI and should mobilize finance and technical know-how for such an AI adoption.

Furthermore, the complexity of AI systems could pose a barrier for adoption; top management support can help to overcome the resistance to change and allocate resources effectively for AI implementation in the company. Organizations with strong support from top management for AI adoption stand a higher chance of achieving a successful outcome [15]. With a clearly established vision for AI adoption, key workers will be appointed to take charge and assign financial and other resources to the project, especially during the implementation phase. In other words, top management support creates a transparent and conducive environment, thus encouraging employees to adopt and embrace AI technology. According to those statements, hypothesis H3 is:
H3: Top management support has a significant positive relationship with AI adoption among PLMCs in Malaysia.

2.3.2.2 Financial Readiness

As the implementation of AI technology often requires significant investment, organizations must be financially ready and committed to allocating sufficient budget for it. Lim & Seng [20] investigated AI adoption in Malaysian SMEs, particularly in accounting, and confirmed that firms with structured financial planning were more successful in implementing AI solutions. Their research emphasized that financial readiness reduces perceived risks and enhances management's confidence in AI investments, leading to higher adoption rates.

Financial readiness drives both exploitative and exploratory innovation in AI adoption. Companies with sufficient financial resources could allocate budgets not only for immediate AI deployment but also for continuous experimentation and scaling, which indicates that, beyond the initial implementation costs, financial readiness also entails ensuring long-term sustainability [27]. In other words, budgets must be allocated for continuous AI system maintenance, periodic upgrades, and ongoing employee training, in order for the organizations to maintain continuity of adoption in a rapidly evolving technological landscape.

Companies with stronger financial capabilities are better equipped to invest in AI infrastructure, talent, and long-term innovation [26].

Thus, financial stability allows firms to take calculated risks in AI adoption, leading to greater innovation, particularly in capital-intensive sectors such as manufacturing. A well-structured funding strategy, supported by robust financial forecasting, is vital for the successful deployment and scalability of AI initiatives in the manufacturing sector. According to those statements, hypothesis H4 is:
H4: Financial readiness has a significant positive relationship with AI adoption among PLMCs in Malaysia.

2.4.3 Environmental Aspect

2.4.3.1 Government Support

Government support is another key determinant in fostering AI adoption in manufacturing. Governments can influence AI adoption through policies, financial incentives, and infrastructure development. In Malaysia, the government has launched several initiatives aimed at promoting digital transformation, including AI adoption in the manufacturing sector. These initiatives provide financial assistance, tax incentives, and access to training programs that help companies build the capacity to implement AI technologies [28]. Public funding could help bridge the gap between theoretical AI advancements and practical applications. Without such financial aid, many cutting-edge AI projects, especially those requiring huge computational power, would struggle to move beyond academia.

Government policies also contribute to creating an enabling environment by providing the necessary infrastructure and reducing the financial barriers for smaller firms. Studies indicate that government support enhances the willingness of firms to invest in new technologies such as AI, especially in developing countries where financial resources and technical expertise might be limited [29]. Government supportive plans and policies should be introduced to create a conducive atmosphere to facilitate the propagation of AI and management of its implications, thus encouraging the intentions for AI adoption.

Moreover, clear and supportive regulations are essential to ensure AI is developed and deployed responsibly, fostering innovation while mitigating risks. AI has implications for a wide range of issues, such as data privacy, security, and algorithmic transparency [30], where the government can intervene by developing guidelines and frameworks to address legal and ethical concerns related to AI implementations. Without clear regulations, public skepticism may hinder adoption due to fears of bias, privacy violations, or misuse. By providing well-defined regulations that reduce uncertainty of future compliance requirements, governments would foster trust and confidentiality in AI technology, enabling organizations to adopt it more readily. Therefore, the following hypothesis, H5, is developed.
H5: Government support has a significant positive relationship with AI adoption among PLMCs in Malaysia.

2.4.3.2 Competitive Pressure

Competitive pressures refer to the external market forces from rivals that influence the organization's intention to adopt AI in order to stay relevant and maintain a competitive edge [31]. The rapid evolution of AI technologies has become a defining force in reshaping industries and organizational practices. Market competition pressure serves as a significant catalyst for organizations to explore and implement AI solutions that enhance innovation, efficiency, and adaptability [31].

Market turbulence, which is a specific form of competitive pressure, drives human resource professionals to adopt AI technologies [32]. The study finds that in volatile market environments, where rapid hiring, skill mismatch, and employee turnover are prevalent, AI tools help streamline recruitment, improve decision-making, and personalize employee engagement [32]. This competitiveness is necessary to attract and retain talent amid turbulence and accelerates AI adoption.

Empirical evidence from the food supply chain sector demonstrates how intelligent agent technology (a subset of AI) supports decision-making and operational efficiency. The study confirms that competitive pressures compel firms to seek technologies that can provide real-time insights and automate logistics operations [33]. In this highly competitive and time-sensitive industry, AI adoption is driven by the need to respond to supply-demand fluctuations, minimize waste, and enhance traceability.

In competitive markets, organizations are pressured to simultaneously improve existing processes (exploitative innovation) and pursue novel offerings (exploratory innovation). A manufacturing firm may use generative AI to design more efficient product prototypes or optimize production scheduling in response to competitors' faster time-to-market [27]. Manufacturing

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companies are operating in a fiercely competitive market where continuous innovation is essential. Therefore, the following hypothesis, H6, is developed.

H6: Competitive pressure has a significant positive relationship with AI adoption among PLMCs in Malaysia.

2.5 Research Framework

Figure 1 presents the conceptual framework for this study, illustrating the relationships between the determinants influencing AI adoption among Malaysia's PLMCs. The framework proposes that IT capability, complexity, top management support, financial readiness, government support, and competitive pressure serve as independent variables that impact AI adoption as the dependent variable. Together, these six (6) independent variables are hypothesized to have a significant relationship with AI adoption among the PLMCs in Malaysia. The adoption of AI is considered the dependent variable, as it reflects the degree to which these organizations implement AI technologies in their business operations, thus contributing to enhanced productivity, innovation, and competitiveness in the industry.

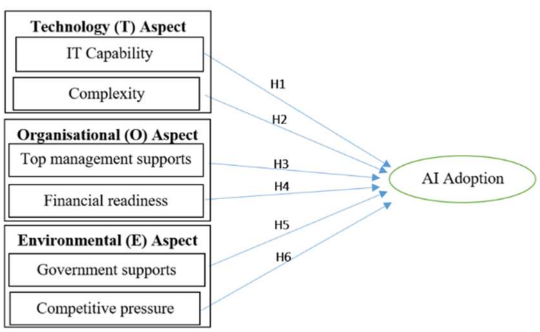

Figure 1: Conceptual Framework

3. METHODOLOGY

3.1 Research Design

This study aims to examine the determinants that influence AI adoption in PLMCs in Malaysia. The research adopts the TOE framework to explore six key determinants: IT capability, system complexity, top management support, financial readiness, government support, and competitive pressure. A quantitative approach is employed, using a structured questionnaire targeted at the top managers, front-line managers, or supervisors who are knowledgeable about their organization's technological and strategic operations. Respondents are selected through simple random sampling to ensure broad representation across various manufacturing subsectors. The study covers the collection of data through online surveys and subsequent analysis using descriptive statistics, correlation, and multiple regression techniques. Figure 2 reveals the research process flowchart.

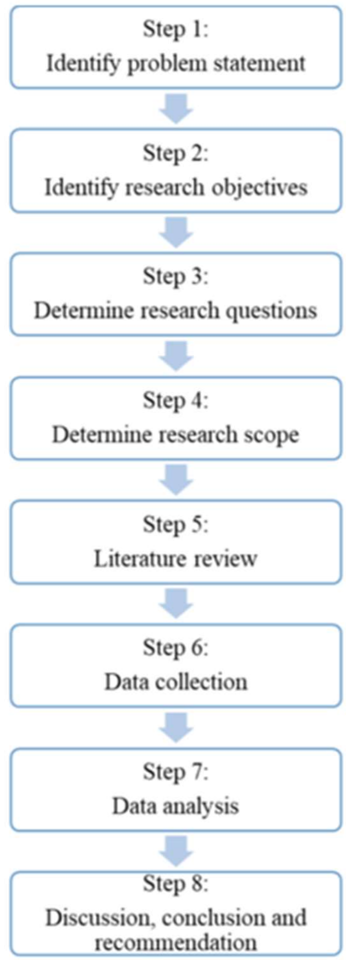

Figure 2: Research process flowchart

3.2 Population and Sample

The population of this study consists of PLMCs in Malaysia that are engaged in some form of technological advancement or innovation. The decision to focus on PLMCs in the Main Market of Bursa Malaysia was made to capture a broad variation in corporate size and industry type, particularly among firms with high market capitalization. These companies generally represent the largest and most resource-rich entities in Malaysia. Given that the adoption of AI technologies often requires substantial financial and technological resources, larger firms are more likely to act as early adopters of such innovations [34]. Moreover, large firms tend to shape industry trends and set technological standards, reinforcing their role as first movers in innovation.

As shown in Bursa Malaysia, a total of 219 companies are listed on the Industrial Products & Services sector [4], one of the dominant sectors in the Bursa Malaysia Main Market, which involves manufacturing companies, industrial product manufacturers, construction engineering firms, and automotive businesses, thus representing the PLMCs. This sector was selected because it represents the most established and resource-capable manufacturing organizations in Malaysia, which are likely to have the financial and technological capacity to adopt AI technologies [14].

For this study, the simple random sampling was chosen as the most suitable probability sampling method. This technique allows the researcher to select the samples randomly from the population of PLMCs in Bursa Malaysia, which are the companies categorized under the Industrial Products & Services sector in the Main Market. This ensures that each member of the population has an equal chance to be selected. Furthermore, the population is sufficiently homogeneous for simple random sampling as the PLMCs are pre-assigned into a specific sector and operated under similar regulatory requirements by Bursa Malaysia. Oversampling was employed here to mitigate the non-response bias.

A sample size of 200 respondents was targeted to achieve a sufficient level of precision and reliability. This sample size aligns with the recommendation of Krejcie and Morgan [35] (Table 3.1), who suggested that for a population of approximately 220, a minimum of 140 respondents is adequate to attain a 95% confidence level with a 5% margin of error. The slightly larger target ensures a higher confidence in statistical analysis and accounts for potential non-responses or incomplete data.

3.3 Research Instrument

In research works, the research instrument is a tool used to collect, measure, and analyze data related to a specific research problem. It provides a systematic means to gather information that is reliable, valid, and consistent with the study's objectives [36]. The choice of instrument depends on the research design, type of data required, and nature of the variables being studied.

Whereas the most commonly used instrument for quantitative research is a structured questionnaire, which consists of standardized responses that can be statistically analyzed [37]. The instrument for data collection in this study employs a set of self-administered questionnaires adapted from various past studies [14. 38], modified to align with the scope of the present study and research objective. The survey questionnaire for this study was developed in English and consists of five sections (A, B, C, D, and E) to gather information on the independent variable (IV) and dependent variable (DV) in the proposed research model, plus demographic information.

Section A covered respondents' demographic profiles and basic company information such as age, gender, position held, company size, and type of business. Whereas Section B will measure the IV of the TOE framework, focusing on the Technological aspect. Respondents answered about the company's IT infrastructure, technical expertise, and the alignment of IT with business objectives.

Section C covered IV, which focuses on the Organizational aspect: Questions will measure the level of commitment and involvement of top management, and financial readiness for AI adoption, including strategic vision, financial resource allocation, and fostering a culture of innovation. Section D measured the IV on the degree of the Environmental aspect that encouraged technology diffusion. This section assessed the perceptions of company leaders regarding government policies, infrastructure development, and rival pressure aimed at facilitating AI adoption. Lastly, Section E measured the degree of AI adoption. The adoption of AI technologies will be measured in terms of AI integration into business operations, such as automation, data analytics, and machine learning applications. Respondents indicated the extent of AI implementation within their organizations.

All items in the questionnaire were measured by a 7-point Likert scale (1=very low, 7=very large or 1=strongly disagree, 7=strongly agree) except for the demographic information. A study by Russo et al (2021) pointed out that the 7-point Likert scale is more reliable than the 5-point Likert scale. The 7-point scale allows greater dispersion and finer distinctions in participants' attitudes or opinions. Respondents used more points on the 7-point scale (average 5.48) than on the 5-point scale (average 3.99), suggesting that more options allowed them to express more nuanced views.

To assess content validity, the researcher sent the research questionnaires to two (2) experts, both of whom have more than 10 years of working experience as managers in a manufacturing company. They separately evaluated the test items to determine whether they comprehensively reflect the subject being studied. This process helps ensure that the instrument is both relevant and representative. At the same time, the two (2) experts with English proficiency had helped to validate the language accuracy, as the research questionnaire was written in English.

The pilot test had been carried out by distributing the research questionnaire to 30 respondents, where Cronbach's Alpha coefficient had been computed to determine the internal consistency reliability. For the total 23 measured items (together IV and DV), the computed Cronbach's Alpha overall value was above 0.9, which is defined as an excellent reliability and validity scale, indicating the survey questionnaire of this study is suitable for the respondents and has acceptable reliability and validity.

3.4 Data Collection Procedure

Data collection was conducted through online distribution of the questionnaire, utilizing Google Forms as the survey platform to ensure accessibility and ease of response. The primary advantage of online surveys is that they can reach a wide audience, regardless of their geographic location, especially among managers of PLSs [39]. This data collection technique would save a significant amount of time and be cheaper compared to in-person interviews or paper-based surveys.

Usually, PLMCs nowadays have their respective company website, which is accessible via the company email. Prior to the survey, respondents had been contacted through this official company email to request their permission and support to conduct the online questionnaire for this study. Each invitation included an introductory message explaining the purpose of the study, confidentiality assurances, and estimated completion time. Participation was voluntary, and respondents were informed that no personally identifiable information would be disclosed. This ethical approach ensured compliance with Universiti Tun Hussein Onn Malaysia's ethical research standards and data protection policies.

Respondents targeted included top management members, managers, and supervisors who are familiar with their organization's digital transformation strategy and AI-related initiatives. Each company was represented by one respondent to avoid duplication and ensure consistency in organizational-level responses. The researcher followed up with reminder emails after two weeks to improve response rates and maintain sample adequacy. Besides that, the questionnaire had been pre-tested with a small sample (pilot test) to assess its clarity and reliability before full deployment.

3.5 Data Preparation and Execution Protocol

Prior to statistical analysis, the collected data were screened for completeness, missing values, and outliers. Responses with substantial missing data were removed from the dataset. Data coding and cleaning procedures were performed using Microsoft Excel before being imported into SPSS Version 29 for analysis.

The study utilized survey responses from 126 respondents representing publicly listed manufacturing companies in Malaysia. The dataset consisted of demographic information, TOE determinants, and AI adoption measures. Since all variables were measured using a 7-point Likert scale, no normalization procedure was required. Statistical analyses were performed using IBM SPSS Statistics Version 29. Correlation analysis and multiple regression analysis were conducted using default parameter settings with a significance level of 0.05.

3.6 Data Analysis

The collected data had been analyzed using descriptive statistics (e.g., mean, standard deviation) to summarize the demographic characteristics of the respondents and the main variables of interest. Inferential statistical techniques had been employed to test the relationships between the independent variables (IT capability, complexity, top management support, financial readiness, government support, and competitive pressure) and the dependent variable (AI adoption). Specifically, correlation analysis was used to assess the strength and direction of relationships among variables, while multiple regression analysis was conducted to determine the extent to which the independent variables influence AI adoption. By incorporating multiple predictors, the model provides a more comprehensive understanding of complex relationships within the data. The strength and significance of these relationships are indicated by

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the regression coefficients (β values), which show the direction and magnitude of the effect of each IV on the DV [40].

4. FINDINGS AND DISCUSSIONS

4.1 Current state of the AI adoption level among PLMCs in Malaysia

The first objective of this study is to determine the level of AI adoption among the PLMCs in Malaysia. The mean value is calculated to evaluate the level of central tendency of the responses received for each item.

Table 1: Descriptive Statistics – Level of AI Adoption

Variable Items	Mean	Level of Agreement	Std. Deviation	Data Dispersion
LAIA1	5.49	High	.901	Low
LAIA2	5.83	High	.827	Low
LAIA3	5.36	High	1.262	High
LAIA4	5.64	High	1.023	High
LAIA5	5.86	High	0.797	Low
Average	**5.63**	**High**	**0.962**	**Low**

Table 1 shows the mean and standard deviation for the items of the Level of AI Adoption (LAIA). The mean and standard deviation are 5.63 and 0.962, respectively, indicating that the PLMCs in Malaysia are highly in agreement with the adoption of AI technology in their organizations and exhibit low dispersion in their agreement levels.

These results show that the PLMCs in Malaysia, on average, had positive attitudes toward AI adoption in their organizations, with an average score of 5.63 for all the statements. It is a positive sign of AI adoption in Malaysia that the PLMCs are prepared for the utilization and integration of AI into their daily operations, which are necessary for realizing long-term benefits. Furthermore, this could be the main driving force for PLMCs in Malaysia to overcome the low adoption rate issue.

4.2 Relationship between TOE determinants and AI adoption among PLMCs in Malaysia

The second objective of this research was to identify the key determinants that influence the AI adoption among PLMCs in Malaysia. In order to achieve this objective, correlation analysis has been used to determine the relationship between the TOE determinants and AI adoption. The results in Table 2 show that there is a significant correlation between all the key TOE determinants (IV) toward AI adoption among the PLMCs. However, the findings in this study showed that relationship strengths are in the range of 0.294 to 0.397, which were defined as weak to weak-moderate magnitude. In other words, the TOE determinants were, although significant, weakly to moderately influencing the level of AI technology adoption.

Table 2: Summary of Correlation between IV and DV

Spearman's rho	avITS	avC	avTMS	avFR	avGS	avCP	avLAIA
avITS	1.000						
avC	0.273^{**}	1.000					
avTMS	0.680^{**}	0.371^{**}	1.000				
avFR	0.601^{**}	0.396^{**}	0.700^{**}	1.000			
avGS	0.470^{**}	0.383^{**}	0.497^{**}	0.604^{**}	1.000		
avCP	0.531^{**}	0.315^{**}	0.492^{**}	0.438^{**}	0.543^{**}	1.000	
avLAIA	0.347^{**}	$.0.294^{**}$	0.383^{**}	0.397^{**}	0.356^{**}	0.372^{**}	1.000

The correlation analysis results have been summarized in Table 2. These findings suggest that while the determinants are related to AI adoption at the bivariate level, the strength of these relationships is limited. The weak bivariate correlations indicate that AI adoption among PLMCs is not driven by any single factor in isolation; no determinants exhibit a strong standalone effect in this observation. Instead, the AI adoption is influenced by multiple interacting factors.

This outcome is consistent with prior regional and global studies [41], which suggest that global awareness of AI is high, although the full-scale implementation remains limited. PLCs appear to adopt AI cautiously, despite their stronger financial positions and access to capital markets. Most likely, it is due to their concerns related to the implementation risks, system complexity, data governance, and, most importantly, the expectations of their shareholders. This cautious approach reflects the reality that AI adoption in manufacturing is not merely a technological upgrade but a strategic transformation that affects core operations, workforce structures, and long-term competitiveness.

In the Malaysian context, this weak adoption level also reflects the limited spreading of the national digital transformation landscape, where Industry 4.0 initiatives are still maturing. While government policies such as Industry4WRD and MyDIGITAL provide strategic direction, the organizational-level execution remains uneven

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across firms. Again, this is consistent with the low adoption rate among PLMCs, which was observed during the demographic analysis of the organizations' profiles.

By applying the TOE framework, the results demonstrate that AI adoption is driven by an interaction of technological readiness (IT capability, complexity), organizational commitment (top management support, financial readiness), and environmental forces (government support, competitive pressure). Table 3 depicts the results of the hypothesis. Based on the respective p-value below 0.001, all the IVs have a significant relationship with AI adoption. However, Hypothesis H2 was rejected due to the positive correlation coefficient, which deviated from the initial proposed expectation.

Table 3: The Result of Hypotheses

Label	Hypothesis	Spearman's rho correlation	Rejected / Accepted
H1	IT capacity has a significant positive relationship with AI adoption among PLMCs in Malaysia.	0.347	Accepted
H2	Complexity has a significant negative relationship with AI adoption among PLMCs in Malaysia.	0.294	Rejected
H3	Top management support has a significant positive relationship with AI adoption among PLMCs in Malaysia.	0.383	Accepted
H4	Financial readiness has a significant positive relationship with AI adoption among PLMCs in Malaysia.	0.397	Accepted
H5	Government support has a significant positive relationship with AI adoption among PLMCs in Malaysia.	0.356	Accepted
H6	Competitive pressure has a significant positive relationship with AI adoption among PLMCs in Malaysia.	0.372	Accepted

4.2.1 Technological Aspect

4.2.1.1 IT Capability and AI Adoption

The findings reveal that ITC had a significant positive relationship with AI adoption, supporting Hypothesis H1, which implied that manufacturers with stronger IT infrastructure and integrated digital systems were more likely to adopt AI technologies.

This result aligned with the previous studies by Dong & Cao [26] and Badghish & Soomro [18], which emphasize that AI adoption is dependent on foundational IT readiness in the organizations. In manufacturing environments, AI may help to support optimal sequence and workload planning, where human experience reaches its limit due to sheer variety and possible options. Organizations face difficulties in integrating AI with legacy systems such as MRP, ERP, or even the business intelligence ESS (Executive Support System) platforms, if lacking adequate IT infrastructure.

This finding is particularly important for Malaysia PLMCs, as it highlights that AI adoption is an evolutionary process rather than a standalone initiative. Organizations that have already invested in digitalization and automation are better positioned to progress toward AI-enabled smart manufacturing. Therefore, it is prudently important to understand the view that AI adoption builds upon earlier stages of digital maturity.

4.2.1.2 Complexity and AI Adoption

The results show that complexity has a significant but positive relationship with AI adoption, thus rejecting Hypothesis H2. This indicates that higher perceived complexity

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associated with AI systems still increases the likelihood of adoption among PLMCs. An unexpected finding of this study is that complexity demonstrated a positive rather than negative relationship with AI adoption. This contradicts the original hypothesis and much of the existing literature [18, 27], which generally regards complexity as a barrier to technology adoption. One possible explanation is that publicly listed manufacturing companies possess greater organizational resources, technical expertise, and financial capacity compared with smaller firms. Consequently, complex AI systems may be perceived not as obstacles but as strategic investments capable of generating competitive advantages. Firms operating in technologically intensive manufacturing environments may view complexity as an indication of technological sophistication and future capability development rather than implementation difficulty.

Nevertheless, this observed positive correlation aligned with research suggesting complexity can motivate technology adoption. Organizations facing operational inefficiencies often pursue AI solutions to manage complexity [42]. This relationship may also reflect the availability of resources toward greater innovation capability [34], such as those that typically existed in larger organizations. Furthermore, some organizations may view complex data ecosystems as strategic assets to be leveraged through AI [43]. Therefore, complexity could serve such duality characters as both constraint and catalyst, toward the adoption of AI. The weak correlation suggests, however, that while complexity may initiate or encourage the AI adoption attempts, successful implementation likely depends on additional factors that are beyond the scope of this study.

In the Malaysian manufacturing context, the resource-rich PLMCs might be adopting AI specifically to mine value from their existing complex data ecosystem. Thus, the complexity is not a barrier; instead, it has become an unrealized asset to motivate AI adoption.

4.2.2 Organizational Aspect

4.2.2.1 Top Management Support and AI Adoption

The results demonstrated that TMS is positively associated with AI adoption, as outlined in Hypothesis H3. This demonstrates the importance of leadership commitment to pushing AI efforts among PLMCs.

This finding supports the prior studies that argue that top management influences strategic priorities, resource allocation, and organizational culture [15, 32]. In PLMCs, the support by top management for emerging technology is particularly crucial, as the investments into such AI technologies can have long payback periods and initially affect bottom-line metrics, which are prone to attacks by their shareholders.

Positive and strong top executive support indicates an organization's readiness for change, fighting against the resistance and validating AI investments, which is more likely in a large organization. In the Malaysian context, this result indicates that AI adoption is more likely to happen when leaders and top management members view AI as a strategic capability, instead of just a cost center or experimental technology.

4.2.2.2 Financial Readiness and AI Adoption

The findings supported Hypothesis H4 by showing that financial preparedness has a positive relationship with AI adoption. In other words, companies with adequate funding and well-organized investment planning are more likely to use AI technologies.

This result was consistent with earlier research [20, 26], which found that adopting AI entails significant initial and continuing expenses, such as system maintenance, software acquisition, infrastructure investment, and talent development. Financial readiness lowers the perceived risk and makes it possible for businesses to continue AI projects past the pilot phase.

Financial readiness also gives Malaysian PLMCs the freedom to test AI applications without sacrificing operational stability. This result supported the idea that implementing AI is a long-term strategic commitment rather than a one-time investment.

4.2.3 Environmental Aspect

4.2.3.1 Government Support and AI Adoption

The results supported Hypothesis H5 by showing that GS significantly increases the adoption of AI. This demonstrates how crucial outside institutional support is for promoting technological innovation.

Government programs that lower adoption barriers and demonstrate the commitment of the country to digital transformation, including Industry4WRD, digital grants, tax incentives, and AI-related training courses. This result is in line with research done in developing nations, where government intervention is essential for reducing capacity and financial limitations [20, 26].

The results, however, also imply that without strong organizational readiness, government support is insufficient on its own. Businesses must actively utilize available incentives and match them with internal strategies in order to effectively adopt AI.

4.2.3.2 Competitive Pressure and AI Adoption

The findings support Hypothesis H6 by confirming that AI adoption is positively correlated with competitive pressure. Businesses that are up against fierce competition are more likely to use AI to boost productivity, cut expenses, and improve responsiveness.

This result is in line with earlier research that contends that market competition spurs innovation [25, 32]. Competition from regional economies like China, Vietnam, and Thailand increases the need for operational excellence and technological differentiation in Malaysia's export-oriented manufacturing sector.

In addition to encouraging PLMCs to adopt AI, competitive pressure speeds up decision-making processes as businesses strive to retain shareholder confidence and market relevance.

4.3 Impacts of the TOE determinants on the AI adoption among PLMCs in Malaysia

The third objective of this research is to examine the impact of the TOE determinants on the AI adoption among PLMCs in Malaysia. The researcher used a multiple regression model to examine the linear relationship between the TOE determinants (IV) and AI adoption (DV). The coefficients of the multiple linear regression (MLR) model are estimated using the sample data.

As shown in Table 4, the results of the regression analysis showed that the only determinant statistically significantly influencing the adoption of AI was CP ($\beta = 0.483$, $p < 0.001$) (shown in Table 5.4), underscoring the predominance of the environmental aspect. According to recent studies, organizations adopt advanced digital technologies primarily in response to market dynamics and competitive intensity rather than internal readiness alone [44, 45]. CP has been demonstrated to play a crucial role in accelerating the adoption of AI and Industry 4.0 in manufacturing contexts, especially in emerging economies where businesses are typically risk-averse [33].

Table 4: Results of the regression analysis

Aspect	TOE Determinants (IV)	Significant level	Beta value
Technology	IT Capability (ITC)	0.448	-0.119
	Complexity (C)	0.531	-0.057
Organization	Top Management Support (TMS)	0.074	0.327
	Financial Readiness (FR)	0.275	0.166
Environment	Government Support (GS)	0.337	-0.120
	Competitive Pressure (CP)	<0.001	0.483

On the other hand, when included concurrently in the regression model, ITC, C, TMS, FR, and GS were not found to have significant effects. This result implies that while these TOE determinants may have a bivariate relationship with AI adoption, their explanatory power decreases when considered in conjunction with other determinants.

A notable observation is the discrepancy between the correlation and regression results. Although all TOE determinants were significantly correlated with AI adoption, only competitive pressure remained significant in the regression model. This phenomenon may be attributed to overlapping variance among the predictors, particularly between organizational and technological determinants. For example, firms with strong IT capability often also possess higher financial readiness and stronger management support. When these variables are entered simultaneously into the regression model, their unique contribution becomes less distinguishable. Therefore, the findings suggest that technological and organizational readiness function primarily as enabling conditions, whereas competitive pressure acts as the direct trigger that motivates actual AI adoption decisions.

The lack of statistically significant effects for organizational and technological aspects does not mean that they are unimportant. According to earlier studies, internal capabilities like IT infrastructure, financial preparedness, and top management support frequently serve as enabling conditions rather than direct adoption drivers. Their effects may lessen when analyzed concurrently because of overlapping explanatory power [46], implying that organizations may possess adequate resources and capabilities but delay adoption until compelled by competitive dynamics. This interpretation was further supported by the weak to moderate correlations in the bivariate analysis, which suggest that no single internal factor independently influences AI adoption.

From a contextual standpoint, the results show how businesses in the emerging economies adopt technology with caution. Large-scale AI investments by Malaysian PLMCs may be postponed because of perceived risks, return uncertainty, and shareholder expectations. Thus, CP acts as the decisive catalyst that transforms organizational readiness into actual adoption behaviors.

The dominance of competitive pressure can also be explained by the increasingly globalized nature of manufacturing competition. Malaysian manufacturers operate in markets where competitors continuously adopt advanced digital technologies to improve productivity, product quality, and operational efficiency. As firms observe competitors achieving tangible benefits through AI implementation, the perceived risk of not adopting AI becomes greater than the risk of adoption itself. Consequently, competitive pressure becomes a stronger motivator than internal technological or organizational readiness, driving firms to accelerate AI adoption in order to maintain market relevance and long-term competitiveness.

Overall, the regression results offer significant empirical proof that the adoption of AI in Malaysia's manufacturing sector is largely driven by the market rather than internal capability. This supports the arguments that organizational and technological preparedness play supporting but secondary roles in accelerating the adoption of advanced technology, while external competitive dynamics play a dominant role. This finding extended the existing TOE-based literature by showing that the relative importance of TOE dimensions is context-dependent and varies across industries and economic environments.

4.4 Summary of Key Findings

The findings of this study provide several important insights into AI adoption among publicly listed manufacturing companies in Malaysia. First, the descriptive analysis indicates that respondents generally exhibit positive attitudes towards AI adoption, suggesting increasing awareness of AI's strategic value. Second, correlation analysis demonstrates that all six TOE determinants are significantly associated with AI adoption, supporting the relevance of the TOE framework in explaining organizational technology adoption behaviour. Third, despite the significant bivariate relationships, regression analysis reveals that competitive pressure is the only determinant exerting a significant unique influence on AI adoption. This finding highlights the dominant role of environmental factors in driving technology adoption decisions within the Malaysian manufacturing sector. Overall, the results suggest that while technological and organizational readiness remain important supporting conditions, competitive market forces serve as the primary driver of actual AI adoption behaviour.

5. CONCLUSION, IMPLICATIONS AND RECOMMENDATIONS

5.1 Concluding Remarks

This study used the TOE framework to investigate the determinants that influence the adoption of AI among PLMCs in Malaysia. The study attempted to offer empirical insights into how the determinants in the aspects of organization, technology, and environment affect AI adoption decisions in an emerging economy setting by combining descriptive analysis, Spearman's rho correlation analysis, and multiple regression analysis.

Overall, the results of the study show that the research questions and objectives, hypotheses, and empirical findings are in strong alignment. The first research objective aimed to identify the current state of AI adoption level among the PLMCs in Malaysia. The descriptive analysis results indicate that respondents generally held a positive perception toward AI adoption, suggesting favorable attitudes toward the use of AI technologies. However, the actual level of AI adoption remains relatively limited.

In relation to the second research objective, which aimed to determine the relationship between TOE determinants and AI adoption among PLMCs in Malaysia, correlation analysis reveals that all six TOE determinants exhibit significant but weak to moderate-weak relationships with AI adoption, indicating that no single determinant exerts a strong bivariate correlation.

Finally, addressing the third research objective to examine the impacts of the TOE determinants on the AI adoption among the PLMCs in Malaysia, the multiple linear regression results demonstrate that competitive pressure is the only TOE determinant that significantly influences AI adoption, while the remaining technological and organizational aspects do not have significant unique effects when considered simultaneously.

These findings revealed that AI adoption in Malaysia still remains at an infancy and cautious stage, as seen in the bivariate analysis, which shows weak to moderate relationships between TOE determinants and AI adoption. When all the determinants were examined simultaneously, the multiple linear regression results demonstrate that competitive pressure was the only determinant exerting a statistically significant unique influence on AI adoption. Determinants that in the Technology aspect and organization aspect - IT capability, complexity, top management support, financial readiness, and government support - were found not to independently drive adoption decisions, but to play the supportive roles. These findings suggested the core prudent role of environmental forces to push organizational willingness into actual AI adoption behavior. Therefore, organizations appear to adopt AI primarily as a strategic response to market pressure in highly competitive environments, rather than as a purely technology-driven initiative.

From a management point of view, the dominant role of competitive pressure in AI adoption reveals that aligning AI initiatives with competitive strategy is of greater importance than focusing solely on internal capability development. From a policy standpoint, the results suggest that competition-enhancing and ecosystem-oriented policies may be more effective in stimulating AI adoption, instead of direct incentives alone.

Collectively, these findings indicate that AI adoption among Malaysian PLMCs is not solely determined by technological capability or organizational preparedness. Rather, adoption decisions are shaped by a combination of internal readiness and external environmental pressures. The results emphasize that organizations may possess the necessary resources and capabilities to adopt AI, but actual implementation is more likely to occur when firms perceive a strategic necessity arising from competitive market conditions. This highlights the importance of considering both organizational capabilities and environmental dynamics when developing AI adoption strategies.

In summary, this study offers solid empirical evidence that the adoption of AI among PLMCs in Malaysia is largely driven by the market rather than by internal capabilities. The study advances knowledge of AI adoption behavior in emerging economies by highlighting the critical role of competitive pressure. It also provides insightful information for academics, practitioners, and policymakers who want to encourage significant and long-term AI adoption in the manufacturing sector. effects.

5.2 Implications

This study provided several significant theoretical implications for studies on the adoption of AI and the application of the TOE framework, especially in relation to PLMCs in developing nations. The findings revealed that the TOE framework was contextually non-uniform in nature by demonstrating that its three aspects did not equally influence AI adoption. Instead, determinants in the technological, organizational, and environmental aspects collectively affect the innovation adoption. The present study showed that the environmental aspect, specifically competitive pressure (CP) had become the dominant influence when all determinants are examined simultaneously. This supports recent TOE-based studies, which argue that environmental pressures often outweigh internal readiness factors in driving advanced digital technology adoption, particularly in competitive manufacturing environments [45].

The complex and multidimensional nature of AI adoption decisions is theoretically explained by the weak to moderate correlations found between TOE determinants and AI adoption. Adoption of AI entails significant levels of uncertainty, organizational change, and strategic risk, which is a different ballgame compared to incremental or low-risk technologies. The weak bivariate relationships support recent theoretical claims that multivariate and context-sensitive explanatory frameworks are necessary for advanced digital technologies [40, 44], suggesting that AI adoption cannot be sufficiently explained by linear & single-factor models, thus requiring more contextualization of theories of innovation adoption across various economic and institutional settings [47]. Accordingly, companies in developing nations like Malaysia might exhibit strategies that are more cautious, driven by the market, and prioritizing competitive survival over internal capability optimization.

The prevalence of CP suggests that managers should see the adoption of AI as a strategic necessity in response to market competition rather than just a technological advancement. Even though leadership support and IT infrastructure investments are still crucial, they might not result in the adoption of AI unless businesses see a distinct competitive threat or strategic disadvantage. Therefore, rather than responding to competitive disruptions after the fact, top management should be actively monitoring competitor behavior, industry benchmarks, and global technological trends in order to be proactive in their strategic business planning.

For policymakers, this result suggests that incentives and capability-building initiatives might not be enough to encourage the adoption of AI. Instead, AI adoption may be more successfully stimulated indirectly by policies that increase competitive intensity, such as promoting export orientation, global trading, and industry benchmarking. Industry associations and collaborative platforms can facilitate knowledge exchange and resource synergy in order to promote a culture of innovation and adoption throughout the PLMCs ecosystem.

5.3 Recommendations

Despite the valuable contributions of this study, several limitations provide opportunities for future research. First, the cross-sectional nature of the study restricts the ability to examine changes in AI adoption behaviour over time. Future studies should employ longitudinal research designs to better understand the evolution of AI adoption and establish stronger causal relationships among TOE determinants. Second, future research should explore potential mediating and moderating relationships among the determinants, particularly the role of competitive pressure in influencing the effects of technological and organizational readiness. Third, future studies should expand the scope beyond publicly listed manufacturing companies to include SMEs and service-based industries, thereby improving the generalizability of the findings. Finally, future research should investigate the impact of AI adoption on organizational performance outcomes such as productivity, innovation capability, operational efficiency, and financial performance.

Beyond these limitations, future studies may also investigate non-linear, moderating, and mediating relationships among TOE determinants. The results of this study suggest that CP, which was categorized in the external environment aspect, may act as a catalyst to activate the internal readiness factors. Future research could examine whether organizational factors mediate the impact of environmental pressures or whether competitive pressure moderates the relationship between technological or organizational readiness and AI adoption. A deeper theoretical understanding of AI adoption mechanisms may be possible by incorporating interaction effects or structural equation modeling techniques.

Furthermore, comparative studies involving SMEs, service industries, and different national contexts would provide a broader understanding of AI adoption behaviour. The relative importance of TOE determinants may change for SMEs due to different constraints and motivations, such as resource constraints or increased reliance on government support. The generalizability of AI adoption theories would be improved by comparative studies across industries and organization sizes. Besides, cross-country comparative research is recommended to investigate how institutional environments and market competitiveness influence AI adoption decisions across various national contexts. It would be possible to determine whether the dominant role of competitive pressure seen in this study is context-specific or generally applicable by comparing emerging economies with developed economies.

In addition, future research could consider incorporating an objective to measure AI adoption toward organizations' performance outcomes, like return on investment, operational metrics, or productivity indicators, thus building more actionable insights into the drivers and consequences of AI adoption in the manufacturing sector and beyond.

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