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Factors Influencing Artificial Intelligence Adoption in Publicly Listed Manufacturing Companies: A Technology, Organisation, and Environment Approach

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Abstract

This study examines the factors influencing artificial intelligence (AI) adoption in publicly listed manufacturing companies in Malaysia. Specifically, three factors are investigated based on the technology, organisation, and environment (TOE) framework: information technology (IT) capability, top management support, and government support. Using a questionnaire survey of 127 respondents from publicly listed manufacturing companies in Malaysia, this study shows that top management support and government support significantly affect AI adoption in publicly listed manufacturing companies. However, the results show that IT capability does not significantly influence the AI adoption of publicly listed manufacturing companies. Thus, the findings provide evidence of the influence of IT capability, top management support, and government support on AI adoption in publicly listed manufacturing companies. In addition, the findings of this study contribute to the existing literature on AI adoption in publicly listed manufacturing companies in Malaysia.

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1. Introduction

Artificial Intelligence (AI) has expanded over the years, and it is now in high demand in the business environment. The aim of AI is to provide and maintain intelligent products, services, and interactions through information sharing to enable collaboration or optimum and lasting benefit (Gretzel, Sigala, Xiang, & Koo, 2015), and it can take many forms (Brynjolfsson & Mcafee, 2017). AI technologies have transformed all types of industries, and the manufacturing industry is no exception. The introduction of AI can increase the performance of manufacturing companies by offering various advantages such as quality control, shortening design time, minimising the waste of resources, improving the reuse of production, and conducting predictive maintenance, among others. Thus, adopting AI can benefit companies by promoting corporate success and providing a strategic benefit (Ransbotham, David, Philipp, & Reeves, 2017).

Over the last five years, the worldwide development of AI has proceeded at a tremendous rate. However, many countries, including Malaysia, still face difficulties with AI, particularly with its adoption within industries, because it features more complex data and requires deep learning and understandability. This observation is supported by Ramaswamy (2019), who noted that the process of AI adoption by the manufacturing industry is slow and remains a challenge. This raised the question: What factors contribute to the low level of AI adoption among manufacturing companies?

This study aims to examine the factors that influence AI adoption among publicly listed manufacturing companies in Malaysia. Based on the TOE framework, this study examines three factors, namely, IT capability, top management support, and government support for AI adoption among publicly listed manufacturing companies. The findings of this study provide an understanding of the factors that can influence AI adoption in the business environment, particularly in the manufacturing industry. The remainder of this paper is organised as follows. Section 2 presents a review of the literature relevant to this study. This is followed by Section 3, which explains the research design. Section 4 presents the results, and Section 5 concludes this paper.

2. Literature Review

AI is a system in which a program is used to build a sophisticated device with the same basic features as humans. AI is defined as computers' ability to carry out tasks by showing intelligent, human-like behaviour and behaving logically by sensing the environment and taking actions to attain certain goals (Russell & Norvig, 2010). AI was first developed in the United States in the 1950s and is one of the primary innovations recognised by organisations worldwide (Haefner, Wincent, Parida, & Gassmann, 2021). John McCarthy first coined the phrase artificial intelligence in 1956, when he organised the first academic conference on the subject, defining AI, brilliant computer programs, as the science and engineering of intelligent machines (McCarthy, 1959). However, studies on AI have reported a low level of AI adoption. For example, Gnaneswaran (2019) reported that only 26% of Malaysian businesses have started adopting AI.

Various studies have attempted to determine the factors influencing AI adoption among companies, such as technology readiness (e.g., Damerji and Salimi (2021); Damerji. (2020)) and accounting practices (Moll & Yigitbasioglu, 2019). Other studies have linked top management support, an absence of AI skills, and workers' fear of the transition to AI adoption rates (Ransbotham et al., 2017). For example, Alsheibani, Cheung, and Messom (2018) examined a lack of detail regarding which elements a company's workers consider when forming their opinions on the use and adoption of AI technology. The reason is a scarcity of studies devoted to determining employees' preferences regarding AI adoption. From the TOE framework perspective, studies have suggested a link between AI adoption and companies' IT capability, top management support, and government support (Sulaiman, Cheung, & Messon, 2019).

IT capability is defined as a distinctive collection of human resources-based skills, orientations, attitudes, motivations, and behaviours that have the potential, under appropriate circumstances, to contribute to achieving specified tasks and impacting business success (Willcocks & Feeny, 2006). Stoel and Muhanna (2009) described IT capability as a complex set of IT resources, competencies, and know-how created in the business process to enable companies to coordinate activities and use IT resources to achieve their desired results. IT resources are a collection of infrastructure resources that serve as the foundation for existing and future business systems. IT infrastructure resources are traditionally connected with a collection of technology resources such as hardware, operating systems, networks, telecommunication technologies, data, and key applications.

Several studies, such as that of Garrison, Wakefield, and Kim (2015), have found a positive relationship between IT capability and AI adoption. This is because strong IT capabilities eliminate complex problems and allow the IT department to deliver AI technology quickly and effectively. In addition, IT capability is a major determinant of innovation adoption, and many studies have found a favourable association between IT capability and AI adoption. Wu, Wang, and Lin (2007) also found a positive relationship between IT capability and AI adoption. This is because AI systems require the firm's network applications and hardware to have better IT capability relative to current technologies.

Furthermore, the estimated cost and time involved with AI deployment are smaller when the AI is compatible with current IT. The better the IT capability, the easier it is to adopt AI. Additionally, it allows the successful implementation of AI applications on the existing infrastructure. Companies can gain a competitive edge by using IT capabilities to improve service delivery, develop new products, processes, and strategies, work faster, eliminate communication barriers within the business, and empower workers to connect with consumers and suppliers (Liu, Huang, Wei, & Huang, 2015). The fast growth of AI in the 4.0 manufacturing industry has led to concerns about manufacturing firms' IT capabilities, which has caused demand for technological skills in manufacturing firms to skyrocket (Seet, Jones, Spoehr, & Hordacre, 2018). Companies require more technological capabilities to achieve a rapid technological transformation in their production environment (Hussain, Mkpojiogu, Mortada, & Yue, 2018). Therefore, we have developed the following hypothesis:

H1: IT capability has a significant positive relationship with AI adoption in publicly listed manufacturing companies in Malaysia.

Another group of studies has shown a positive relationship between top management support and AI adoption. Top management support may help companies embrace technological innovation by creating an environment that facilitates creative thinking and offers opportunities for individuals who practice innovative work (Borgman, Bahli, Heier, & Schewski, 2013). Top management support may also increase transparency by intervening in events and actively engaging in IT management or by communicating the importance of a certain idea or technology and fostering the value of innovation (Borgman et al., 2013). Furthermore, top managers, departmental managers, and leaders are the ones to satisfy this desire for innovation. Studies aim to help top managers understand and develop company strategies such as awareness, job overload reduction, and company expansion.

Hage and Dewar (1973) found a positive relationship between top management support and AI adoption. This is because to implement innovation, it must be supported by managers at upper levels who have the power to assign company supplies and resources. Without top manager support, AI adoption cannot be implemented because there will be no authorities who push for advances in the organisation's technology. This view is supported by Elbanna (2013), who found that during the implementation phase, manager support must be reliable and continuous, or the project could collapse. The explanation is that managers are required to appoint key workers to oversee certain tasks, particularly at higher levels, and assign financial and other resources to the development (Tung, 1987). Top management support is strongly linked to AI adoption. Greater levels of support from top management provide a stronger IT environment for AI adoption and eliminate AI technology difficulties. Therefore, the following hypothesis is developed:

H2: Top management support has a significant positive effect on AI adoption in publicly listed manufacturing companies in Malaysia.

Past studies have shown that government support has a positive effect on AI adoption. To a certain extent, the direction of the regulatory framework influences the overall industrial structure. One key study suggested that during the AI adoption period, government support is a crucial determinant. Agrawal, Gans, and Goldfarb (2018) found a positive relationship between government support and AI adoption. This is because the government can create a conducive atmosphere for AI and facilitate the propagation of AI and the management of its implications through policies and procedures. The government should introduce supportive plans and policies to encourage the commercial use of emerging technology and set new guidelines for implementing new technologies.

The implementation of emerging technologies is a dynamic process, and the government's framework is crucial. Furthermore, AI has implications for a wide range of issues such as privacy, security, and ethical culture. Consequently, AI requires a healthy legal environment; thus the fast growth of AI technology requires the simultaneous expansion of security, law, ethics, and governance. The key research suggests that during the AI adoption period, government intervention is a crucial determinant. The results also reveal that government support would boost investment at the sector level, directly affecting sustainable company growth. According to the MITI (2018) industrial policy blueprint, the Malaysian government could provide support in the form of collaboration through public-private partnerships and investment-friendly taxes, which would increase AI adoption among manufacturing companies in Malaysia. Through government support, particularly through funding incentive programs provided by the Malaysian government, the adoption of AI has increased significantly. Therefore, the following hypothesis is developed:

H3: Government support has a significant positive effect on AI adoption in publicly listed manufacturing companies in Malaysia.

3. Methodology

3.1. Sample Selection

Data were gathered from Bursa Malaysia (the Malaysian stock exchange) regarding a total of 265 companies in the manufacturing industry listed on Bursa Malaysia. The growing requirement for a representative statistical sample in empirical research has generated a need for an efficient technique for calculating sample size. To meet this need, Krejcie and Morgan (1970) developed a simple reference table for calculating the sample size for a given population. The required sample size is thus 155 (Krejcie & Morgan, 1970). Stratified random sampling was carried out. First, the population was divided into mutually exclusive categories that were valid, acceptable, and relevant in the scope of the study. Hence, the sample size collected in this study of 127 out of 155 respondents is justified. Since this study examined publicly listed manufacturing companies, the top managers and lower-level managers or supervisors were the respondents on behalf of their company. In other words, each respondent represented one company.

Industrial products and services were selected because they involve automation and machinery and thus represent the manufacturing industries. Besides, industrial products and services including automotive, plantations, pharmaceuticals, retail and consumer items, port operations, and logistics are all important users of AI technology in the industry (PWC, 2018).

3.2. Research Instrument

This study utilised a questionnaire as the research instrument. The questionnaire was developed by adapting the research instruments administered in similar studies conducted by Reich and Benbasat (1990); Chau and Tam (1997); Chang, Hwang, Yen, and Lian (2006); Garrison et al. (2015) and Oliveira, Thomas, and Espadanal (2014). The questionnaire for this study consisted of five sections: A, B, C, D, and E. Section A covered respondents' demographic profiles and basic company information, including details such as age, gender, position in the company, highest education, level of adoption, and type of business.

Section B measured the degree to which top management involvement, direction, and support played a crucial role, as they explicitly and actively help introduce any new technology. This included top management support of employees regarding AI technologies and related resources. Section C measured IT capability and the degree to which innovation was perceived as consistent with the existing values, past experiences, and needs of potential adopters.

Section D measured the degree to which government involvement encouraged technology diffusion and the company's exposure to regulations that increased or removed barriers to introducing new technologies or systems. For example, the government could establish supportive plans and policies to promote the commercial applications of new technologies and create new rules for developing new technologies. Lastly, Section E reviewed the degree of adoption of AI technology, determining whether the companies had already adopted AI technology and the level of existing technology in the organisation. For each item, a 5-point Likert scale was used, ranging from 1 (strongly disagree) to 5 (strongly agree). Each section included five statements.

3.3. Data Collection

The data was gathered from the target respondents via online questionnaire administration. Prior to data collection, this study was given ethics approval and office consent to conduct the research. According to Sekaran and Bougie (2016), there are several advantages to online questionnaire administration, the primary one being that it can reach a large audience, even individuals who may be difficult to reach through other channels. As a result, this data collecting technique can save a significant amount of time, money, and energy. For this study, respondents were contacted via email to enlist their permission and support to conduct the online questionnaire about publicly listed manufacturing companies. Several manufacturing companies from 9 business types were approached via email to request their permission and assistance in administering the questionnaire.

The biggest problem was that some of the contacted respondents did not answer, which delayed data gathering because the survey instrument could not be widely distributed. As Sekaran and Bougie (2016) stressed, one of the issues when delivering online questionnaires is a poor response rate. Hence, the respondents who did not answer the first email were sent a second email a week later. The online questionnaire did not require the respondents' email addresses. Hence the respondents remained anonymous. In the end, 127 questionnaires were successfully gathered, showing an 81% response rate.

4. Results

Table 1 illustrates the demographic profiles regarding the type of business, level of AI adoption, and company age. The data analysis shows that with regards to the type of business, the majority of respondents represented companies in building materials and industrial materials, each with 24 respondents representing 18.9% of the sample. This was followed by chemicals, with 19 (15%), wood and wood products, with 13 (10.2%), the metals industry, with 12 (9.4%), packaging material, with 11 (8.7), industrial engineering, with 10 (7.9%), and auto parts, with 9 (7.1%). In comparison, the diversified industrial category had the lowest number of respondents, with a total of 5 out of 127. Concerning AI adoption, the result shows that most respondents (63) were planning to adopt AI technology in the near future. This is due to most companies still using traditional methods. On the other hand, 42 of the respondents said their organisations had already adopted AI technology.

Table 1. Companies' profile.

Characteristic	Description	Frequency	Percentage
Type of business	Auto parts	9	7.1
	Building material	24	18.9
	Chemicals	19	15.0
	Diversified industrial	5	3.9
	Industrial engineering	10	7.9
	Industrial materials	24	18.9
	Metals industry	12	9.4
	Packaging material	11	8.7
	Wood and wood products	13	10.2
Level of adoption	Already adopted	42	33.1
	Not yet adopted	22	17.3
	Will adopt in near future	63	49.6
Age of company	0-2 years	7	5.5
	3-5 years	30	23.6
	6-9 years	31	24.4
	10-14 years	38	29.9
	More than 14 years	21	16.5

Nevertheless, 22 respondents' companies had no plans to adopt AI technology. This could be due to the company already being in a comfortable position and being reluctant to change. Other reasons for not adopting AI technology include higher AI costs and longer returns for Industry 4.0 processes and technologies, as well as a considerable scarcity of the necessary talents, skills, knowledge, and understanding to operate AI technology (MITI, 2018).

Lastly, the results show that the age of most respondents' companies is between 10-14 years, with 38 out of 127 respondents selecting this option. On the other hand, 7 out of 127 respondents reported that their company was in the lowest age category of 0-2 years. It can be concluded that most publicly listed companies in the manufacturing industries have been in business for more than three years.

Table 2 depicts the descriptive statistics for the study's dependent variable, AI adoption. Based on the five statements, the respondents, on average, had positive attitudes toward AI adoption in their organisation, with a mean score of 4.61. Concerning the individual statements, respondents appeared to mostly agree that they preferred AI technology to traditional systems, with a mean score of 4.67. This is followed by statement five that they recommended adopting AI technology (mean score = 4.66). The statement with the lowest mean score of 4.54 was the statement that claimed their organisation was expected to adopt AI technology in the near future. Overall, the respondents generally agreed that adopting AI technology in their organisation would be a positive development.

Table 2. Descriptive statistics - AI adoption.

Statement	Mean	Std. Deviation
I preferred to adopt AI technology rather than use the traditional system	4.67	0.560
Once I have used AI technology, I will continue to use it	4.57	0.590
My organisation is expected to adopt AI technology shortly	4.54	0.640
I think that I made the correct decision to adopt AI technology in my organisation	4.63	0.550
Overall, I would recommend adopting AI technology in an organisation	4.66	0.570
Average score for all statements	4.61	0.580

Table 3 depicts the descriptive statistics for IT capability. Based on the five statements, the respondents generally agreed that IT capability had a positive relationship with AI adoption (mean score = 4.60). The respondents most agreed with the statement that AI technology was compatible with their organisation's management style (mean score = 4.65). Statements 1, 2, and 4 each had the same results, with mean scores of 4.60. This indicates that the respondents strongly agreed that AI technology was compatible with the existing devices used by the organisation, with the current hardware, and with the way the respondents liked to manage organisational productivity. However, the lowest mean score of 4.54 was for the statement that AI technology was compatible with their business operations and customer needs.

Table 3. Descriptive statistics for IT capability.

Statement	Mean	Std. Deviation
AI technology is compatible with the existing devices used by the organisation	4.60	0.630
AI technology is compatible with the current hardware	4.60	0.550
AI technology is compatible with business operations and customer needs	4.54	0.610
AI technology is compatible with the way I like to manage organisational productivity	4.60	0.520
Overall, AI technology is compatible with the organisation's management style	4.65	0.530
Average score for all statements	4.60	0.570

Next, we proceeded to determine whether IT capability influenced AI adoption in publicly listed manufacturing companies in Malaysia. A correlation analysis was performed to support the results reported above. Table 4 shows the result of the correlation analysis between IT capability and AI adoption. There is a significant, positive, moderate correlation between IT capability and AI adoption ($r = 0.687$, $p < 0.001$).

Table 4. Correlation analysis between IT capability and AI adoption.

Variable	AI Adoption	
	r	p-value
IT Capability	0.687	0.000

Table 5 depicts the descriptive statistics for top management support. Based on the five statements, the respondents generally agreed that top management support has a positive relationship with AI adoption (mean score = 4.77). According to the individual statements, respondents appear to mostly agree that AI technology is a convenient way for organisations to make better decisions, with a mean score of 4.83. The statements that AI technology enables them to accomplish organisational tasks much quicker (mean score = 4.80) and that it improves workers' productivity (mean score = 4.79) also obtained high scores. While respondents least agreed with the statement that AI technology is useful for managing an organisation (mean score = 4.69). Overall, the respondents generally agreed with all the statements relating to top management support, as reflected by the fact that the mean score for each statement was higher than 4.

Table 5. Descriptive statistics - top management support.

Statement	Mean	Std. Deviation
AI technology is a convenient way for the organisation to improve its decision making	4.83	0.380
AI technology enables me to accomplish organisational tasks much more quickly	4.80	0.440
AI technology improves workers' productivity	4.79	0.410
AI technology gives benefits to managers/supervisors in achieving organisational success	4.74	0.440
Overall, AI technology is useful for managing the organisation	4.69	0.460
Average score for all statements	4.77	0.430

Next, a correlation analysis was conducted to support the above results and determine whether top management support influences AI adoption in publicly listed manufacturing companies in Malaysia. Table 6 shows the results of the correlation analysis between top management support and AI adoption. The results indicate a significant, positive, moderate correlation between top management support and AI adoption (r = 0.688, $p < 0.001$).

Table 6. Correlation analysis between top management support and AI adoption.

Variable	AI Adoption	
	r	p-value
Top Management Support	0.688	0.000

Table 7 depicts the descriptive statistics for government support. Over the five statements, the mean score reported by the respondents was 4.61, indicating their belief that government support has a positive relationship with AI adoption. The respondents indicated the highest level of agreement with the statement that government support is crucial to the adoption of AI technology, with a mean score of 4.69. Next, the respondents agreed that using AI technology would enhance government agencies by allowing them to deliver services and interact with their citizens more transparently and effectively (mean score = 4.65). The statement that they believed government support was crucial to adopting AI as a digital priority to achieve high outcomes that result in organisational transformation showed a mean score of 4.61.

Table 7. Descriptive statistics - government support.

Statement	Mean	Std. Deviation
The government has provided guidelines, policies, and procedures to regulate AI technology	4.57	0.610
The government has proposed the right regulations for accountability, privacy, explainability, and social responsibility that will ensure AI technology is safe and trusted	4.54	0.530
Using AI technology will enhance government agencies by allowing them to deliver services and interact with their citizens more transparently and effectively	4.65	0.480
I find government support is crucial to the adoption of AI as a digital priority to achieve high outcomes that result in organisational transformation	4.61	0.550
Overall, government support is crucial to the adoption of AI technology	4.69	0.470
Average score for all statements	4.61	0.530

The second-lowest scoring statement was that the government had provided guidelines, policies, and procedures to regulate AI technology, which had a mean score of 4.57. Meanwhile, the statement that the government had proposed the right regulations for accountability, privacy, explainability, and social responsibility to ensure AI technology was safe and trusted had a mean score of 4.54. This is because respondents had less faith in government regulation. Thus, it is important for the government to have transparent rules and regulations.

Next, a correlation analysis was conducted to support the above results and determine whether government support influences AI adoption in publicly listed manufacturing companies in Malaysia. Table 8 shows the results of the correlation analysis between government support and AI adoption. The results indicate a significant, positive, high correlation between government support and AI adoption ($r = 0.743$, $p < 0.001$).

Table 8. Correlation analysis between government support and AI adoption.

Variable	AI Adoption	
	r	p-value
Top Management Support	0.743	0.000

A one-way ANOVA was used to establish the overall significance of the model before conducting the multiple regression analysis. The F-test results show whether there is a linear relationship between all the independent variables and the dependent variable (when taken together). The one–way ANOVA test results are shown in Table 9, with an F-ratio of $F(3,123) = 70.855$, $p < 0.001$. This shows that at least one of the three independent variables examined in the model has a significant linear association with AI adoption. In other words, at least one of either IT capability, top management support, or government support affects AI adoption.[1]

Table 9. One-way ANOVA for AI adoption.

Model		Sum of Squares	df	Mean Square	F	Sig.
	Regression	386.637	3	128.879	70.855	0.000
1	Residual	223.725	123	1.819		
	Total	610.362	126			

Note:
a. Dependent Variable: AI Adoption.
b. Predictors: (Constant), Top Management Support, IT Capability, Government Support.

Further, as Table 10 shows, the $R^2 = 0.633$, which means that the model explains approximately 63.3% of the total variation in the dependent variable. This indicates that 63.3% of the variation in the respondents' results on AI adoption was explained by the variation in IT capability, top management support, and government support for AI adoption. Overall, the model can thus be considered significant and appropriate.

Table 10. Multiple regression model.

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	0.796	0.633	0.625	1.349

Following the goodness of fit tests, multiple linear regression was carried out to test this study's hypotheses. Table 11 depicts the coefficient results of the multiple linear regression analysis carried out on the model.

Table 11. Multiple regression results.

Model		Unstandardised Coefficients		Standardised Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	-1.224	1.770		-0.691	0.491
	IT.Cap	0.190	0.090	0.187	2.125	0.036
	TMS	0.399	0.102	0.300	3.925	0.000
	GovS	0.451	0.100	0.402	4.502	0.000

Note
a. Dependent Variable: AI Adoption.
b. Predictors: (Constant), Top Management Support, IT Capability, Government Support.

Based on the results, two of the three independent variables tested had a significant effect on the dependent variable. Top management support ($\beta_1 = 0.399$, $t = 3.925$, $p < 0.001$) and government support ($\beta_1 = 0.451$, $t = 4.502$, $p < 0.001$), positively and significantly influence AI adoption. This signifies that respondent have a strong belief regarding the positive effect of top management support and government support on AI adoption. In contrast, the results of the regression model show that IT capability had no significant relationship with AI adoption ($\beta_5 = .190$, $t = 2.125$, $p = 0.036$), meaning that IT capability has the least effect on AI adoption and does not significantly affect it. The weightage of the independent variables' (IT capability, top management support, and government support) influence on the dependent variable was indicated by the coefficient or the beta-value, β_i, of each independent variable. The significant factor with the highest beta-value was government

[1]The reliability test and normality test were performed before testing the hypotheses. The results of Cronbach's Alpha test showed all variables were above 0.80, indicating that the variables were normal. The normality test also showed that skewness and kurtosis values for all variables were within the range of -1.309 to 0.733, indicating that the mean scores for AI adoption, IT capability, top management support, and government support were all normally distributed.

support, with a coefficient of $\beta_4 = 0.451$. This was followed by top management support ($\beta_2 = 0.399$) and finally IT capability ($\beta_3 = 0.190$). This indicates that government support had the most significant impact on AI adoption compared to the other factors.

5. Conclusion

This study examined the factors that influence AI adoption in publicly listed manufacturing companies in Malaysia. Specifically, this study examined the effects of IT capability, top management support, and government support on AI adoption among publicly listed manufacturing companies. The first objective was to examine the effect of IT capability on AI adoption in publicly listed manufacturing companies in Malaysia. Similar to Chen (2019), this study also found an insignificant relationship between IT capability and AI adoption. Hence, H1 was rejected. However, this finding does suggest that IT capability gives good results when people in the organisation are responsible for IT diffusion. Furthermore, the effect of IT capability would be greater if all parties involved adopted AI successfully. The implication is that IT capability is not a major factor that influences successful AI adoption. The study has proved that IT capability is only one minimal factor out of hundreds that may be more important to AI adoption in the country. Nevertheless, although this study concludes that IT capability does not support AI adoption based on the data gathered about Malaysia's publicly listed manufacturing companies, investigations based on data from other sectors may have different results. The role of IT capability has not been exhaustively addressed in the current technology adoption literature, and further study is needed to investigate the influence of IT capability on AI adoption.

The second objective was to examine the effect of top management support on AI adoption in publicly listed manufacturing companies in Malaysia. The results showed a significant and positive relationship between top management support and AI adoption, which was the second most influential among the three investigated components. Top management support has been shown to have a favourable impact on the adoption of technological advancements. Similar findings have been observed in previous studies (e.g., Wade and Hulland (2004); Elbanna (2013)) reflecting that having good managerial support may lead to the successful adoption of AI technology in an organisation. The presence of top management support may have a positive effect on the organisation as a whole. The implication is that support from superiors is crucial to AI adoption in an organisation. This result is consistent with other studies that concluded that top management support is important in successfully implementing AI adoption in an organisation.

The third objective was to examine the effect of government support on AI adoption in publicly listed manufacturing companies in Malaysia. The results showed a significant and positive relationship between government support and AI adoption, which appeared to be the most highly weighted among the three components. This finding indicates that government support is a significant factor that contributes to AI adoption. The government's framework is thus crucial to implementing emerging technologies while making users believe that AI adoption can make their time and efforts more valuable. Governments and companies must develop practical ways to educate workers about AI in the workplace; AI implementation may benefit all workers both directly and indirectly over time as AI technology evolves. This finding is similar to those of studies that focused primarily on AI adoption, such as Chang et al. (2006). The implication is that government support is a crucial factor in increasing AI adoption. Government support may have already resulted in AI adoption, but the government must fully support the country with AI adoption. AI can help firms operate more effectively, control expenses, and make significant advances in research. Government and public sector innovation can aid in the spread of AI throughout industries.

The findings of this study provide valuable supporting evidence of the effects of IT capability, top management support, and government support in increasing AI adoption in publicly listed manufacturing companies in Malaysia, where AI use is still relatively lacking compared to Western or more developed countries. In addition, this study contributes to the literature by applying TOE theory. A TOE-based methodology for evaluating an organisation's readiness for technology adoption has previously been suggested and verified for use in large organisations (Abeysinghe & Alsobhi, 2013). Identifying crucial success criteria and specifying alternative frameworks that would serve as guides for the adoption of AI technology are suggested as future research directions.

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