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Readiness for Artificial Intelligence Adoption in Malaysian Manufacturing Companies

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Abstract

The advancement of artificial intelligence (AI) and its growing societal importance are reshaping decision-making processes and policy analysis roles. This study examines the readiness of manufacturing companies in Malaysia to embrace AI technology, considering its potential to enhance decision-making, productivity, quality control, job automation, and data analysis. Focusing on the Technology, Organization, and Environment (T-O-E) readiness framework, the research investigates the relationship between these dimensions and AI adoption readiness among manufacturing companies in Shah Alam, Selangor, Malaysia. AI adoption readiness serves as the dependent variable, while technological, organizational, and environmental readiness dimensions act as independent variables. The study applies the T-O-E framework to AI readiness and proposes a framework for assessing AI readiness at the manufacturing level. It identifies factors influencing readiness within the technological, organizational, and environmental dimensions, including relative advantage, compatibility, resources, competitive pressure, top management support, and government regulations. Through rigorous analysis, patterns, trends, and correlations are revealed, highlighting a significant link between the T-O-E readiness dimensions and AI adoption readiness. Notably, organizational readiness emerges as a key driver of AI adoption in Malaysian manufacturing companies. The results of this investigation have broad implications, offering suggestions to improve organizational preparedness and unlock AI's potential benefits for businesses in the industrial sector. Additionally, the research lays the groundwork for further studies on AI readiness across various industries and international contexts. As AI becomes increasingly integrated into manufacturing processes, adaptive businesses gain competitive advantages on a global scale. These advantages include increased productivity, informed decision-making, streamlined quality control, improved customer satisfaction, and potential contributions to economic growth. The study concludes by recommending strategies to reinforce organizational readiness and emphasizes the need for future research to deepen understanding of AI adoption readiness in the manufacturing industry. The integration of AI technology offers benefits such as enhanced productivity, decision-making, quality control, and customer satisfaction, granting businesses a competitive edge in the digital landscape and increasing stakeholder interest.

Keywords: Technology Readiness, TOE, Artificial Readiness, Artificial Intelligence

Introduction

This chapter introduces the concept of Artificial Intelligence (AI) and its application in manufacturing, highlighting its benefits and the current AI readiness in Malaysia. AI is defined as computer programs that mimic human thought and behavior, enhancing decision-making and automating complex tasks in manufacturing (Baltzan, 2019). Examples include intelligent systems, machine learning, and robotic process automation, which improve productivity, quality control, and operational efficiency (Gurudatta, 2022). AI applications, such as ChatGPT and machine learning algorithms, are utilized by companies like BMW and Danone to optimize processes and enhance customer satisfaction (Hill-Yardin, 2023; Uzir et al., 2023). AI's benefits include increased efficiency, predictive maintenance, better production planning, and improved product quality (Javaid, 2022; Ayvaz, 2021). Malaysia, ranked 36th in the Government AI Readiness Index, has made progress in AI adoption through initiatives like Industry4WRD and NextBigTech Asia (Oxford Insights, 2021; Bernama, 2020). Factors influencing AI readiness in manufacturing include technology, organizational context, and environmental elements (DePietro, 1990). Despite the progress, there is a need to explore how organizational, technological, and environmental factors impact AI adoption in Malaysian manufacturing industries. This research aims to fill this gap and provide insights for future AI adoption (Ryfors et al., 2019).

Artificial Intelligence (AI) adoption in manufacturing companies faces several significant challenges. A major obstacle in Malaysia is the lack of leadership skills and tools for effective AI integration (Digital News Asia, 2019). Leaders often struggle to understand AI's potential and how to align it with their business strategies, which hampers AI adoption (Alsheibani, 2020). Additionally, inadequate technology infrastructure and resources pose a barrier, as organizations need the right tools and skilled personnel to implement AI effectively (Wahab et al., 2018). Data availability and quality issues further complicate AI adoption, as decentralized and inconsistent data hinder AI's effectiveness (Bowman et al., 2019). The shortage of technically trained staff, particularly experienced data scientists and machine learning specialists, also impedes progress (Mikalef, 2021). Furthermore, resistance to new technologies, especially among older employees, and the high costs associated with AI implementation and maintenance present additional challenges (Merhi, 2023; Hechler, 2020). These issues highlight the need for comprehensive strategies to enhance technological, organizational, and environmental readiness for AI adoption in manufacturing. The research aims to investigate:

1. The relationship between technological readiness dimensions and AI adoption readiness,
2. The relationship between organizational readiness dimensions and AI adoption readiness,
3. The relationship between environmental readiness dimensions and AI adoption readiness.

The study is significant for various stakeholders: it helps organizations evaluate their preparedness for AI adoption by assessing their current capabilities, infrastructure, and processes, identifying strengths and weaknesses related to data availability, technological infrastructure, skill sets, and cultural readiness. For employees, the study raises awareness about the impact and potential of AI technologies on their roles and work environment. For researchers, it enhances the understanding of AI adoption readiness in manufacturing, providing valuable guidelines for future research and practical applications in Malaysian industries. Lastly, for governance and future adopters, the study offers insights into AI adoption readiness at the manufacturing level, supporting national initiatives like the New Intelligent Malaysia agenda and fostering an ecosystem that maximizes the benefits of AI technologies, thus driving economic growth, improving efficiency, enhancing product quality, and promoting safety.

There are numerous factors affecting a manufacturing company's AI adoption readiness, with the TOE (Technology-Organization-Environment) model explaining these influences (Alsheibani, 2018). This model emphasizes the significance of technology, organizational characteristics, and the external environment in new technology implementation (DePietro et al., 1990; Ryfors, 2019). Technological readiness dimensions such as relative advantage and compatibility influence AI adoption, while organizational readiness is influenced by top management support, resources, and firm size. Environmental readiness involves competitive pressure and government regulatory issues (Ryfors, 2019; Chatterjee, 2021). The TOE framework has been validated in various fields, demonstrating its suitability for investigating innovation adoption at the organizational level (Sheshadri Chatterjee et al., 2021). Studies have shown that technological readiness dimensions (relative advantage and compatibility) positively influence AI adoption (Pizam, 2022; Gao, 2022), while top management support and resources are critical organizational readiness factors (Bahtia, 2021; Zoll, 2022). Environmental readiness factors, including competitive pressure and government regulations, also play a significant role in AI adoption (Mokhtar, 2022). Therefore, the hypotheses in this study propose relationships between these dimensions and AI adoption readiness in Malaysian manufacturing companies as outlined below:

Hypothesis H1: There is a relationship between relative advantages and artificial intelligence adoption readiness in manufacturing companies in Malaysia.

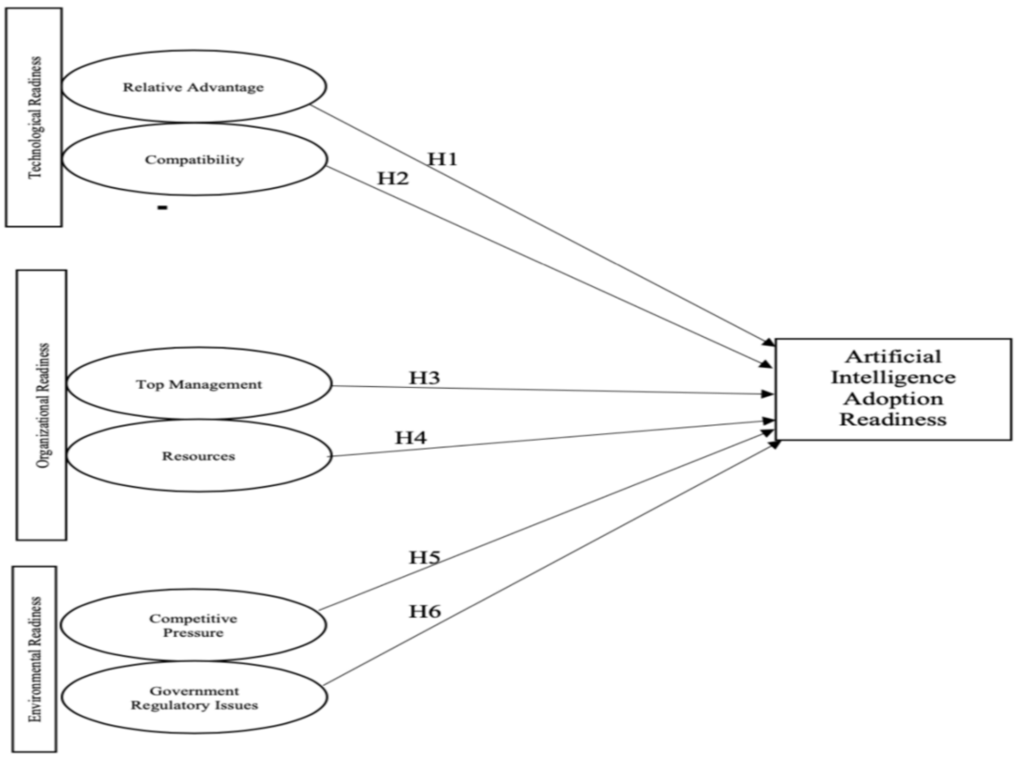
Hypothesis H2: There is a relationship between compatibility and artificial intelligence adoption readiness in manufacturing companies in Malaysia.

Hypothesis H3: There is a relationship between top management and artificial intelligence adoption readiness in manufacturing companies in Malaysia.

Hypothesis H4: There is a relationship between resources and artificial intelligence adoption readiness in manufacturing companies in Malaysia.

Hypothesis H5: There is a relationship between competitive pressure and artificial intelligence adoption readiness in manufacturing companies in Malaysia.

Hypothesis H6: There is a relationship between government regulatory issues and artificial intelligence adoption readiness in manufacturing companies in Malaysia.



ource: Adapted from Artificial Intelligence Adoption: AI-readiness at Firm-Level by AlSheibani(2018)

Figure 1. Research Framework for AI Adoption Readiness in Manufacturing Companies in Malaysia

Methodology

The research methodology examines the relationship between technology readiness dimensions (relative advantage and compatibility), organizational readiness dimensions (top management support and resources), environmental readiness dimensions (competitive pressure and government regulatory factors), and artificial intelligence adoption readiness among manufacturing companies in Selangor, Malaysia. It details the research design, population, sampling frame, sampling technique, sample size, unit of analysis, instrument reliability and validity, data collection procedure, and data analysis plan. To test the proposed model and hypotheses, a quantitative method with a correlational design and cross-sectional survey using a questionnaire was employed. The population consists of manufacturing companies in Malaysia, focusing on those in Shah Alam, Selangor, with a sample size of 234 determined via Krejcie and Morgan's table and the Raosoft calculator. The unit of analysis is organizational, targeting top management employees. Data collection involved the online distribution of modified questionnaires, with pretests ensuring validity and reliability. Data analysis, conducted using IBM SPSS, included frequency, factor, correlation, and regression analyses. The demographic details of the respondents are shown in Table 1.

Table 1. Demographic Details of Respondent

Variables	Descriptions	Frequencies	Percentage (%)
Gender	Male	209	89.3
	Female	25	10.7
Age	<25 years old	6	2.6
	26-35 years old	16	6.8
	36-45 years old	40	17.1
	45 years old and above	172	73.5
Working Experience	Less than 2 years	5	2.1
	2-5 years	5	2.1
	5-10 years	14	6
	More than 10 years	210	89.7
Marital Status	Single	13	5.6
	Married	219	93.6
	Others	2	0.9
Highest Level of Education	SPM	1	0.4
	Diploma	6	2.6
	Bachelor's Degree	144	61.5
	Master's Degree	76	32.5
	Doctoral Degree	7	3
Position Held	CEO	167	71.4
	Others	66	28.2
Types of Manufacturing Industry	Food Manufacturing	15	6.4
	Textile	10	4.3
	Rubber & Plastic Products	2	0.9
	Petroleum	1	0.4
	Electric & Electronic	15	6.4
	Beverages & Tobacco	3	1.3
	Automation	28	12
	Others	160	68.4
Numbers of Employees	<5 (Micro)	24	10.3
	6 to 30 (Small)	102	43.6
	31 to 75 (Medium)	21	9
	>200 (Large)	87	37.2
Level of Annual Sales	<Rm300,000	23	9.8
	RM300,000<RM3Million	117	50
	RM3Million<RM20Million	4	1.7
	Million	90	38.5

Measures

The instrument for data collection in this study consists of a set of existing questionnaires adapted from various previous studies, modified to align with the research objectives and questions. The survey, conducted in English, comprises close-ended questions, which are preferred for their time efficiency and ease of response (Sekaran & Bougie, 2016). These questions offer a fixed range of possible answers. The questionnaire is divided into three sections: Section A, which collects demographic and personal information such as gender, age, marital status, highest education level, position held, work experience, and daily internet usage at the workplace; Section B, which measures the independent variables of TOE theory, focusing on technology readiness dimensions (relative advantage and compatibility), organizational readiness dimensions (top management support and resources), and environmental readiness dimensions (competitive pressure and government regulatory issues); and Section C, which focuses on the dependent variable, AI adoption readiness.

Table 2. Measurement of Study

Section A	No. of Items	Scale	Sources
Section A: Demographic Profile	9		
Section B: Relative Advantage	3	5-point Linkert scale	Moore and Benbasat 1991; Vluggen 2005
Compatibility	4	5-point Linkert scale	Peng et al (201; Geezy et al. (2012)
Top Management	3	5-point Linkert scale	Alam, 2016
Resources	4	5-point Linkert scale	Iacovou et al (1995); Aboelmaged (2014); Idris (2015)
Competitive Pressure	3	5-point Linkert scale	Rogers (2003), Yang (2015) Makridakis (2017)
Government Regulatory Issues	4	5-point Linkert scale	Mikalef (2012)
Section C : AI Adoption Readiness	4	5-point Linkert scale	Holmstrom J (2022)

Results

Result of Correlation Analysis

Correlation analysis is a statistical method used to identify the strength and direction of the relationship between two or more variables (Schober, 2023), measured by the correlation coefficient. The Pearson correlation coefficient (r) quantifies the linear connection between two continuous variables, ranging from -1 (perfect negative correlation) to +1 (perfect positive correlation), with 0 indicating no connection. According to Hair (2003), a correlation of .90 to 1.00 indicates a very high positive/negative correlation, .70 to .90 a high correlation, .50 to .70 a moderate correlation, .30 to .50 a low correlation, and .00 to .30 a negligible correlation. The study found highly positive relationships between AI adoption readiness and both technological readiness dimensions (relative advantage, r=.705, and compatibility, r=.793) and organizational readiness dimensions (top management, r=.859, and resources, r=.807). Environmental readiness dimensions showed moderate positive relationships with AI adoption readiness (competitive pressure, r=.568, and government regulatory issues, r=.649). The model summary indicated that the predictors (government regulatory issues, competitive pressure, relative advantage, resources, compatibility, and top management) accounted for 81.8% of the variance in AI adoption readiness. Regression coefficients revealed that top management (Beta=0.448) made the strongest unique contribution, followed by government regulatory issues (Beta=0.249), compatibility (Beta=0.155), competitive pressure (Beta=0.141), and relative advantage (Beta=0.092), while resources did not make a significant unique contribution. Thus, top management, government regulatory issues, compatibility, competitive pressure, and relative advantage are significant predictors of AI adoption readiness in manufacturing companies in Malaysia.

Table 3. Result of correlation analysis between all variables

		Relative_ Advantage	Compa tibility	Top _Mgt	Resources	Competitive _Pressure	Government_ Regulatory _Issues	**Artificial _Intelligence _Readiness**
Relative _Advantage	**Pearson Correlation**	1	.723**	.708**	.574**	.517**	.435**	**.705****
	Sig.		0	0	0	0	0	0
	N	234	234	234	234	234	234	234
Compatibility	**Pearson Correlation**	.723**	1	.782**	.748**	.548**	.565**	**.793****
	Sig.	0		0	0	0	0	0
	N	234	234	234	234	234	234	234
Top _Mgt	**Pearson Correlation**	.708**	.782**	1	.895**	.576**	.559**	**.859****
	Sig.	0	0		0	0	0	0
	N	234	234	234	234	234	234	234
Resources	**Pearson Correlation**	.574**	.748**	.895**	1	.471**	.665**	**.807****
	Sig.	0	0	0		0	0	0
	N	234	234	234	234	234	234	234
Competitive _Pressure	**Pearson Correlation**	.517**	.548**	.576**	.471**	1	.137*	**.568****
	Sig.	0	0	0	0		0.036	0
	N	234	234	234	234	234	234	234
Government _Regulatory _Issues	**Pearson Correlation**	.435**	.565**	.559**	.665**	.137*	1	**.649****
	Sig.	0	0	0	0	0.036		0
	N	234	234	234	234	234	234	234
Artificial _Intelligence _Readiness	**Pearson Correlation**	.705**	.793**	.859**	.807**	.568**	.649**	**1**
		0	0	0	0	0	0	
	N	234	234	234	234	234	234	234

*** Correlation is significant at the 0.01 level (2-tailed).*
** Correlation is significant at the 0.05 level (2-tailed).*

Model Summary

The "Model Summary" section in statistical analyses typically provides a summary of how well the regression model fits the data (Wieditz, 2023), indicating that the predictors (government regulatory issues, competitive pressure, relative advantage, resources, compatibility, and top management) account for 81.8% of the variance in AI adoption readiness (R=0.904, R2=0.818, Adjusted R2=0.813, Std. Error=1.05175). The regression analysis coefficients describe the relationship between the independent variables and the dependent variable, with each coefficient representing the change in the dependent variable for a one-unit change in the related independent variable while holding all other variables constant. Based on Table 4.10.3, top management has the largest beta coefficient (Beta=0.448, $p<0.05$), making the strongest unique contribution to explaining AI adoption readiness, followed by government regulatory issues (Beta=0.249, $p<0.05$), compatibility

(Beta=0.155, $p<0.05$), competitive pressure (Beta=0.141, $p<0.05$), and relative advantage (Beta=0.092, $p<0.05$). However, resources (Beta=0.005, $p>0.05$) did not make a significant unique contribution. Thus, the variables of top management, government regulatory issues, compatibility, competitive pressure, and relative advantage are significant predictors of AI adoption readiness in manufacturing companies in Malaysia.

Table 4. Coefficients

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	Beta	Std. Error	Beta		
(Constant)	-2.3	0.854		-2.728	0.007
Relative_Advantage	0.17	0.084	0.092	2.012	0.045
Compatibility	0.18	0.062	0.155	2.93	0.004
Top_Management	0.54	0.094	0.448	5.69	<0.001
Resources	0	0.061	0.005	0.07	0.944
Competitive_Preassure	0.23	0.061	0.141	3.721	<0.001
Goverment_Regulatory_Issues	0.21	0.034	0.249	6.038	<0.001

Discussion

Based on the results obtained from the correlation coefficient analysis, the findings support the hypotheses for this study, showing a significant relationship between the variables under investigation. The data provide evidence to support the hypothesis that there is a meaningful relationship or correlation between the independent and dependent variables, thereby strengthening the understanding of their relationships and contributing to the study's overall findings. Specifically, the results indicate a positive correlation between relative advantage ($r=.705$, $p<0.05$), compatibility ($r=.793$, $p<0.05$), top management ($r=.859$, $p<0.05$), resources ($r=.807$, $p<0.05$), competitive pressure ($r=.568$, $p<0.05$), and government regulatory issues ($r=.649$, $p<0.05$) with artificial intelligence adoption readiness in manufacturing companies in Malaysia. Therefore, hypotheses H1 through H6, which propose relationships between these factors and AI adoption readiness, are all accepted.

Table 5. Hypothesis Result Table

	Research Hypothesis	Result
Hypothesis H1	There is a relationship between relative advantages and artificial intelligence adoption readiness in manufacturing companies in Malaysia. Relative advantage : (r=.705, p<000, p<0.05)	Accepted
Hypothesis H2	There is a relationship between compatibility and artificial intelligence adoption readiness in manufacturing companies in Malaysia. Compatibility : (r=.793, p<000, p<0.05)	Accepted
Hypothesis H3	There is a relationship between top management and artificial intelligence adoption readiness in manufacturing companies in Malaysia. Top Management : (r=.859, p<000, p<0.05)	Accepted
Hypothesis H4	There is a relationship between resources and artificial intelligence adoption readiness in manufacturing companies in Malaysia. Resources : (r=.807, p<000, p<0.05)	Accepted
Hypothesis H5	There is a relationship between competitive pressure and artificial intelligence adoption readiness in manufacturing companies in Malaysia. Competitive Pressure : (r=.568, p<000, p<0.05)	Accepted
Hypothesis H6	There is a relationship between government regulatory issues and artificial intelligence adoption readiness in manufacturing companies in Malaysia Government Regulatory Issues : (r=.649, p<000, p<0.05)	Accepted

Conclusion

This study explored the relationship between technological, organizational, and environmental readiness dimensions and AI adoption readiness in manufacturing companies in Shah Alam, Selangor, Malaysia. The findings indicated significant relationships among these dimensions, with organizational readiness emerging as the most influential factor in AI adoption. The study provided recommendations for improving readiness, such as investing in technology infrastructure, fostering leadership, and engaging with regulatory bodies. Limitations included time and budget constraints and the use of quantitative methods. Future research should consider a broader range of industries, a larger sample size, and additional qualitative methods to enhance the understanding of AI adoption readiness in the manufacturing sector (Nazarenko, 2022; Makarius, 2020; Hradecky, 2022; Balasubramanian, 2021; Sirait, 2023; Mehri, 2023; Yu, 2023).

Conflict of interest

The authors declare no potential conflict of interest regarding the publication of this work. In addition, the ethical issues including plagiarism, informed consent, misconduct, data fabrication and, or falsification, double publication and, or submission, and redundancy have been completely witnessed by the authors.

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