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Success Factors Impacting Artificial Intelligence Adoption - Perspective from The Telecom Industry in Malaysia

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Abstract — Artificial Intelligence (AI) is playing a growing role in transforming the telecommunications sector by improving customer support, optimizing network performance, and enabling the development of innovative products and services. Despite its advantages, AI adoption in Malaysia's telecom industry faces several challenges, including infrastructure scalability, security issues, and system interoperability. To better understand these barriers, a research study was conducted using a combined Technology Acceptance Model (TAM) and Technology – Organization - Environment (TOE) framework. The study involved surveying network employees from three major Malaysian telecom providers—Telekom Malaysia, Maxis, and CelcomDigi—and examining global best practices to identify key success factors for AI adoption. The framework was validated through statistical techniques such as convergent and discriminant validity tests and Structural Equation Modelling (SEM). The results revealed that organizational and external factors, particularly managerial support, technical capability, market uncertainty, and vendor partnerships, significantly influence AI adoption, with perceived usefulness acting as a key mediator in the adoption process.

Keywords—Artificial Intelligence, Telecommunication, AI adoption, Technological-Organizational-External framework, TOE, Technology Acceptance Model.

I. INTRODUCTION

In today's fast-evolving digital era, technological innovation continues to reshape industries across the globe, with Artificial Intelligence (AI) emerging as a transformative force. AI technologies including machine learning, deep learning and natural language processing considerably simplify business

management, planning and operations by bringing advanced capabilities of data analysis to a large range of sector's current applications [1]. AI has revolutionized several industries, including telecommunication sector. Digital transformation and technological revolution have been the driving forces in telco sector for the past two decades.

The telecommunication sector, in particular, has experienced a significant shift through the adoption of AI technologies. With the ongoing digital transformation and the emergence of 5G, telco companies are under pressure to modernize their infrastructure and maintain competitiveness. AI has the potential to improve telecommunication companies' performance by offering various advantages such as quality control, reduced design time, reduce use of resources, predictive maintenance, 24/7 customer support through chatbots and more. Global telecom giants like AT&T, China Mobile, and SK Telecom have already implemented AI to enhance service quality and uncover new business opportunities. However, in Malaysia, the adoption of AI in telecom remains relatively underexplored. Despite global advancements, there is a noticeable gap in localized research and empirical studies focusing on how Malaysian telcos can effectively implement AI to gain strategic advantages.

This study was initiated to address several critical research gaps. Firstly, although numerous countries have conducted extensive investigations into artificial intelligence (AI) adoption within the telecommunications industry, Malaysia lacks focused and comprehensive studies in this domain. The existing body of work related to Malaysia remains relatively limited. In total, approximately sixty-five scholarly publications, industry reports, and empirical

studies were reviewed to establish the theoretical foundation for this research. Of these, fewer than ten specifically examined AI adoption within the telecommunications sector, as most prior studies predominantly focused on industries such as manufacturing, healthcare, and small and medium enterprises (SMEs). Notably, a recent study by [2] explored AI's role in enhancing Malaysia's telecommunications infrastructure; however, it primarily emphasized implementation strategies and did not incorporate an empirical model to examine behavioral adoption factors.

Secondly, there remains limited understanding within Malaysian telecommunications companies regarding the critical success factors and strategic methodologies employed by leading global operators. For instance, [3] investigated AI adoption within Malaysian network operations using the Technology Acceptance Model (TAM); however, the study did not incorporate organizational and environmental dimensions nor provide statistical validation through an integrated analytical framework. These limitations highlight a significant research gap: the absence of a comprehensive, empirically tested model that combines both the Technology, Organization, Environment (TOE) framework and the Technology Acceptance Model (TAM) to explain AI adoption behavior among telecommunications professionals in Malaysia. In addressing this gap, the present research aims to identify the key success factors influencing AI integration within Malaysian telecommunications companies, assess real-world practices, and propose a structured framework to support efficient and sustainable adoption. By collecting and analyzing data from major local telecom providers, including Telekom Malaysia (TM), CelcomDigi, and Maxis, this study seeks to contribute actionable insights and best practices to accelerate AI transformation in Malaysia's telecommunications sector.

II. CRITICAL REVIEW ON AI ADOPTION BY TELCO COMPANY IN MALAYSIA

The adoption of AI in Malaysia's telecommunication companies has gained momentum in recent years driven by the need for enhanced network efficiency, personalized customer experience, and digital transformation efforts. AI-driven solutions are gradually being implemented by companies like Maxis, CelcomDigi and Telekom Malaysia (TM) to enhance customer service, automate processes and maximize network performance.

For instance, Maxis has implemented GPU-as-a-Service, GPUaaS to support AI model training and enhance computing capabilities. AI-driven network optimization also enables congestion control and predictive maintenance, enhancing reliability and resource efficiency [2, 4].

CelcomDigi has deployed an AI-powered 5G network with automated Radio Access Network, RAN management by collaborating with Huawei. In order to promote innovation across industries, CelcomDigi also founded the AI Experience Centre (AiX).

TM is increasingly utilizing AI in cloud computing, cybersecurity and digital services in line with Malaysia's national AI policy efforts [5].

Nonetheless, there is still a fragmented application of AI. Factors such as high cost of implementation, challenges of integrating legacy systems, scarcity of AI or Artificial intelligence talent and resistance on the part of the organization are examples of challenges facing AI saturation. These obstacles are similar to reports of Malaysian SMEs and manufacturing industry where commitment of the top management and organizational preparedness are revealed as being among the key drivers [6].

On social level, trust is a major element in regard of AI acceptance. According to a Telenor Asia survey, although 76 percent of Malaysians use AI frequently, data protection and abuse issues still take center stage, which means that the sense of safety and openness has a significant role to play [7].

On a comparative level, image adoption patterns in such emerging markets as India, Egypt, and other Southeast Asian countries are as follows: the perceived usefulness (PU) and perceived ease of use (PEOU) have high predictability of adoption, whereas the moderating dimensions of adoption (trust and demography moderators such as age) play a significant role in uptake [8]. This justifies application of hybrid TOE-TAM model, in which the technical, organizational and environmental factors are mediated by element of user perception.

Regulatory and policy environment in Malaysia favours AI innovation. A coherent ecosystem is supposed to be achieved through such endeavours as the National AI Roadmap (2021-2025), the AI Sandbox, and the creation of the National Artificial Intelligence Office. Nonetheless, analysts criticize the existing practice due to the fact that there is no coordination of agencies and this is retarding the maturity of AI in regulated industries such as telecom [9].

Despite potential benefits, AI still not widely used in Malaysia's telco industry. Thus, this study focuses on identifying success factors that drive AI implementation in telco industry while providing a structured framework for overcoming barriers. The expected output of this study will be to identify the success factors of AI adoption based on the developed framework from combination of TOE and TAM.

III. THEORETICAL FRAMEWORK AND HYPOTHESES DEVELOPMENT

The integration of AI technology in the telecommunications sector has significantly enhanced operational efficiency and customer satisfaction. However, the literature review highlights a gap in understanding the key enablers and their interrelationships that drive AI adoption within organizations. To address this, the study proposes a research model that combines the Technology-Organization-Environment (TOE) framework with the

Technology Acceptance Model (TAM) as shown in Fig. 1.



Fig. 1. Combination of TOE - TAM framework.

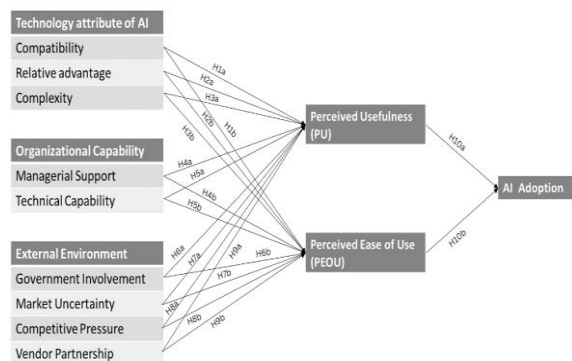


Fig. 2. Proposed research model.

The model categorizes critical success factors into three contexts: technological (compatibility, relative advantage, complexity), organizational (managerial support, technical capability), and external environmental (government involvement, market uncertainty, competitive pressure, vendor partnership). These are linked with TAM factors-perceived usefulness (PU) and perceived ease of use (PEOU)-to examine their influence on AI adoption in Malaysian telecom companies. A set of sub-hypotheses has been formulated to explore how these TOE elements affect PU and PEOU, providing a comprehensive framework as shown in Fig. 2 for successful AI implementation.

A. Compatibility and TAM

Compatibility is the ability to which AI innovation can be incorporated and integrated into organization's existing procedures and infrastructure [10]. Employees prefer to use AI technology if it is suitable with current work practices, even if the organization will need to make some adjustments. This is because incompatibilities typically necessitate significant process adjustments which can be difficult to adopt and require a lot of learning. AI may use virtualization technologies to enable automation and help businesses transition their network infrastructure into software-defined networking. This allows the networks to self-diagnose, self-orchestrate and self-heal. Thus, adoption occurs more quickly with more compatibility. Based on the above discussion, the following sub-hypotheses are proposed:

H1a: Technological compatibility positively influences the perceived usefulness.

H1b: Technological compatibility positively influences the perceived ease of use.

B. Relative Advantage and TAM

The term "relative advantage" describes the apparent value of using AI within a company. Within

the framework of this study, perceived advantages of AI relate to how much AI outperforms rival technologies. The company's desire to embrace new technology is significantly affected by how beneficial the technology is [11]. AI enable the organization to reduce costs, obtain competitive advantage, and opens door for expansion into new markets, boosts top-line profitability, boosts efficiency and amplify AI. Once people know the benefits of AI, they may adapt these developments into their business. This leads to following sub- hypotheses.

H2a: Relative advantage of AI positively influences its perceived usefulness.

H2b: Relative advantage of AI positively influences its perceived ease of use.

C. Complexity and TAM

Complexity means the degree of difficulty and limitations associated with comprehending and utilizing a system [12, 13]. Regarding the adoption of AI, this complexity is viewed as an internal organizational problem that is measured by looking at how much the applications use the AI infrastructure, how long tasks take to complete, how effective intelligent decision-making is, how well the system functions and how well the interface is designed. An organization's usefulness and simplicity of use decline with increasing complexity. This leads to following sub- hypotheses.

H3a: Complexity of AI negatively influences its perceived usefulness.

H3b: Complexity of AI negatively influences its perceived ease of use of AI.

D. Managerial Support and TAM

Managerial support is very important for every beginning, implementation or adopting diverse new technologies in an organization. It emphasizes how senior executives are devoted to and actively involved in leading organizational efforts like AI integration to the business operations. Supports such as cultivating long time vision, strengthening value of the organization, resource optimization distribution, efficient use of resources, fostering positive work environment, boosting each person's sense of effectiveness and overcoming obstacles. Thus, this suggests the following sub-hypotheses.

H4a: Managerial support positively influences the perceived usefulness of AI.

H4b: Managerial support positively influences the perceived ease of use of AI in a telco company.

E. Technical Capability and TAM

Technical capability refers tangible resources such as computer hardware, data and networking infrastructure that are necessary to implement innovations [14]. Technical capability is also group of resources available in company. Intangible assets such

as technical expertise, AI development and collaboration techniques and application methods are considered under technical capacity [15]. Higher technical capacity lowers the integration complexity and enables the quick adaption to AI technology. This suggests the following theory.

H5a: Technical capability positively influences the perceived usefulness of AI.

H5b: Technical capability positively influences the perceived ease of use of AI.

F. Government Involvement and TAM

Regulatory issues are the assistance given by government authority to encourage the adoption of AI. Different governments have different policies for AI adoption. With new regulations for the development of new technologies as well as strategies and policies by government can encourage the adaptation of new technology. The government's assistance creates a climate that is conducive to AI and will accelerate its spread and effects [15]. Hence, this study proposes the sub-hypotheses:

H6a: Government involvement positively influences the perceived usefulness of AI.

H6b: Government involvement positively influences the perceived ease of use of AI.

G. Market Uncertainty and TAM

The adoption of AI in telco sector is significantly shaped by market uncertainty, especially in relation to its impact on organizational decision-making and risk perception. Business may see AI as a challenge as well as an opportunity amid unpredictable market circumstances. On the other hand, by assisting businesses in navigating erratic market changes, AI-driven predictive analytics and automation may improve decision-making, increase productivity and provide them a competitive edge. Organizations with flexible and innovative cultures may embrace AI as a tool for managing uncertainty. This has led to the following sub-hypotheses.

H7a: Market uncertainty positively influences the perceived usefulness of AI.

H7b: Market uncertainty positively influences the perceived ease of use of AI.

H. Competitive Pressure and TAM

Competition pressure has been identified as a component in the transmission of new innovations by extensive empirical study done by [16]. Company's competitive advantages are not long term but its temporary [13]. AI has the power to inspire creativity and open up new possibilities for people and business. The use of AI technologies can provide business competitive advantage. This has led to the following sub-hypotheses.

H8a: Competitive pressure positively influences the perceived usefulness of AI.

H8b: Competitive pressure positively influences the perceived ease of use of AI.

I. Vendor Partnership and TAM

Vendors Partnership are the expertise needed to manage new technology in this case would be AI. Therefore, the adoption of new technology typically linked with IT vendors and cooperative partners. Researchers contend that vendor support act as an external agent to assist an organization in developing its staff knowledge base within the framework of the knowledge-based view. Support from vendor helps in adopting any cutting-edge technology such as AI, Industry 4.0 and more. Employees would find it easier to accept AI integrated technology if they were able to expand their knowledge with the help of vendor and own self [16]. This suggests the following sub-hypothesis.

H9a: Vendor Partnership positively influences the perceived usefulness of AI in a telco company.

H9b: Vendor Partnership positively influences the perceived ease of use of AI in a telco company.

J. TAM-Perceived Usefulness

The term "perceived usefulness" describes a potential user's conviction that utilizing a specific application system would improve work performance. Perceived usefulness encompasses the ideas of subjective norms, image, output quality, work relevance and outcome demonstrability. These predictions led to conclude that people make perceived usefulness judgements in part by cognitively contrasting what a system can do with what they do for their jobs. Consequently, it is believed that a person's intention to adopt a new technology will be influenced by its perceived utility. Thus, this suggests the following theory.

H10a: Perceived usefulness has a positive impact on intention to adopt AI.

K. TAM- Perceived Ease of Use

According to TAM, PEOU predicts employee's intentions to employ a new technology or system. A system's PEOU encourages users to plan to utilize it. The idea of ease of use has been found to predict the intention to use a new system especially the adoption of AI. These discussions have made it clearer that a company's desire to implement AI stems from how simple to use the new technology. This suggests the following theory.

H10b: Perceived ease of use has a positive impact on intention to adopt AI.

IV. Research Methodology

A. Research Instrument

A questionnaire created to gather information on AI adoption which serves as the main research tool for this study. Two framework model is combined in this research which are TOE and TAM. The items are measured using a 5-point Likert scale, with 1 denoting “strongly disagree” and 5 denoting “strongly agree”. There are six sections to the questionnaire. First section collected demographic data while the section 2 assessed technology context like compatibility, complexity and relative advantage. Consequently, in section 3, organization context was tested consist of factors managerial support and technical capability included. Next in section 4, environmental context questions consist of factors which are government involvement, market uncertainty, vendor partnership and competitive pressure included. In section 5, questions regarding acceptance model about perceived ease of use and perceived usefulness were included. Lastly in section 6, questions regarding intention to adopt AI is included.

B. Data Collection

The target population of this study comprises employees from the network departments of telecommunications companies in Malaysia, specifically Telekom Malaysia (TM), CelcomDigi, and Maxis. LinkedIn, email correspondence, and phone conversations were utilized as communication channels to contact the employees of these organizations. According to Chen [13], the minimum sample size in quantitative research should be at least five times greater than the total number of indicators in the measurement scale. Given a total of 33 indicators representing 11 latent factors, the minimum required sample size was calculated as $33 \times 5 = 165$ respondents. The academic purpose of the study was clearly communicated to all potential participants, along with assurances of anonymity and confidentiality. Participants also received detailed instructions on how to complete the response form. These measures were implemented to enhance the overall response rate.

C. Data Analysis

Structural Equation Modelling (SEM), a second-generation multivariate technique, is employed to examine complex relationships between observed variables and latent constructs. SPSS is used to assess the structural and measurement models, while SmartPLS is utilized to obtain SEM values that illustrate relationships between constructs and their indicators. Internal consistency is evaluated using Cronbach's Alpha (α) and Composite Reliability (CR), which help determine the reliability of measurement variables. A Cronbach's Alpha value above 0.7 and a CR value above 0.5 are considered acceptable indicators of internal consistency.

Model reliability is further supported by convergent validity, which ensures that multiple items measuring the same construct are strongly correlated. Convergent validity is assessed through factor loadings and Average Variance Extracted (AVE), both of which should exceed 0.5 to confirm the model's

validity. Discriminant validity ensures that different constructs in a model are truly distinct from one another. It is considered strong when there is little to no correlation between unrelated items. A common way to test it is by comparing the square root of the Average Variance Extracted (AVE) with the correlations among items-if the square root of AVE is greater, discriminant validity is confirmed. Two main approaches to assess this are the Fornell-Larcker method and the HTMT (Heterotrait-Monotrait) ratio.

Survey responses are analyzed using statistical measures like the mean and standard deviation. The mean represents the average value of the responses, while the standard deviation shows how much the responses vary from the average. These measures help to summarize and understand general trends in the data.

Hypothesis testing is conducted using Structural Equation Modeling (SEM) to examine the relationships between variables involved in AI adoption. Important SEM outputs include the path coefficient (β), t-statistic, and p-value. The path coefficient indicates the strength and direction of a relationship between two variables, while the t-statistic tests whether that relationship is statistically significant. A p-value less than 0.05 typically means the result is significant, supporting the alternative hypothesis. To enhance accuracy, a bootstrapping method is used in SmartPLS, where 5,000 resamples of the data are analyzed. This process provides more reliable estimates for the model parameters.

V. FINDINGS

A. Respondents Profile

The target group for this study includes employees from three major telecommunications companies in Malaysia: Telekom Malaysia, Celcom Digi, and Maxis. These companies were selected because they are currently leading the way in AI adoption in the country. Telecom operators play a key role in using AI technologies, especially as the industry moves towards next-generation networks, 5G, and the Internet of Things. These operators are not only major users of AI but also providers of AI platforms and services. To manage complex networks, improve customer satisfaction, and increase efficiency, AI is becoming essential for telecom companies. By integrating AI with 5G, they can also offer advanced solutions to different industries and boost revenue.

To collect data from this target group, a Google Form was used as it is easy to access, quick to complete - under 10 minutes, and suitable for a large group. Following Tatham's guideline for sample size in quantitative research, the required number of responses is five times the number of observed variables. With 33 variables in the model, the minimum sample size is 165. The form was distributed to employees of TM, Celcom Digi, and Maxis on September 23 and kept open until 165 responses were received. The data was then cleaned to remove incomplete or suspicious entries, and all 165 responses

were found valid. In terms of demographics in Table I, 53% of respondents were female and 47% male. Most respondents (51%) worked in network roles, 30% in business development, and 19% in sales. Additionally, 56% had less than 5 years of experience, while 19% had over 10 years of experience.

Table I. Demographic profile.

Demographic Variable	Sub variable	Frequency	Percentage
Gender	Female	87	53%
	Male	78	47%
Scope of Work	Business Development	49	30%
	Sales	32	19%
	Network	84	51%
Years of Experience	<5 years	93	56%
	<10 years	41	25%
	>10 years	31	19%

B. Descriptive Statistic

The reliability of the model was assessed using Cronbach's Alpha and composite reliability. Table II shows the reliability results for all 11 latent factors. All factors had a Cronbach's Alpha above 0.5, indicating acceptable reliability for this research. The Technical Capability factor had the highest reliability (0.799), suggesting that elements like IT infrastructure and technical expertise are key drivers of AI adoption. On the other hand, Market Uncertainty had the lowest reliability (0.554), likely due to the unpredictable nature of factors like consumer behavior, regulatory changes, and competition. These variables can hinder clear decision-making, making it harder for organizations to commit to AI adoption.

Table II. Results for model reliability.

ITEM			Cronbach's Alpha	Composite Reliability
Technological Compatibility	TC	TC1	0.721	0.843
		TC2		
		TC3		
Relative Advantage	RA	RA1	0.774	0.868
		RA2		
		RA3		
Complexity	CO	C1	0.686	0.814
		C2		
		C3		
Managerial Support	MS	MS1	0.779	0.872
		MS2		
		MS3		
Technical Capability	TY	TY1	0.799	0.881
		TY2		
		TY3		
Government Involvement	GI	GI1	0.742	0.853
		GI2		
		GI3		
Market Uncertainty	MU	MU1	0.554	0.818
		MU2		
Competitive Pressure	CP	CP1	0.587	0.829
		CP2		
Vendor Partnership	VP	VP1	0.603	0.834
		VP2		
Perceived Usefulness	PU	PU1	0.744	0.852
		PU2		
		PU3		
Perceived Ease of Use	PEOU	PEOU1	0.737	0.851
		PEOU2		
		PEOU3		

Internal consistency was measured using Composite Reliability (CR). All factors had CR values above the recommended threshold of 0.7 as in Table II. Technical Capability had the highest CR (0.88), indicating strong and consistent measurement. Market Uncertainty had the lowest CR (0.818), which still meets the acceptable threshold. This result aligns with the reliability findings, reinforcing that market uncertainty significantly affects AI adoption in the telecom sector.

The convergent validity of the model was evaluated using factor loadings and Average Variance Extracted (AVE) as in Table III. All 11 latent factors had factor loadings above 0.5, confirming the model's validity. Vendor Partnership indicators (VP1 and VP2) had the highest loadings (0.828 and 0.863), highlighting their strong reflection of that construct. Complexity indicator C1 had the lowest loading (0.706) but was still acceptable, while C2 and C3 showed stronger representation.

All AVE values also exceeded 0.5, indicating that over 50% of variance is captured by their respective constructs. Vendor Partnership had the highest AVE (0.715), while Complexity had the lowest (0.595), aligning with the factor loading results. Overall, both factor loadings and AVE support strong convergent validity for the model.

Table III. Results for convergent validity.

ITEMS			Factor Loadings	AVE
Technological Compatibility	TC	TC1	0.724	0.643
		TC2	0.833	
		TC3	0.843	
Relative Advantage	RA	RA1	0.83	0.687
		RA2	0.85	
		RA3	0.806	
Complexity	CO	C1	0.706	0.595
		C2	0.746	
		C3	0.856	
Managerial Support	MS	MS1	0.861	0.694
		MS2	0.827	
		MS3	0.81	
Technical Capability	TY	TY1	0.827	0.711
		TY2	0.858	
		TY3	0.845	
Government Involvement	GI	GI1	0.845	0.659
		GI2	0.791	
		GI3	0.799	
Market Uncertainty	MU	MU1	0.831	0.691
		MU2	0.832	
Competitive Pressure	CP	CP1	0.84	0.708
		CP2	0.843	
Vendor Partnership	VP	VP1	0.828	0.715
		VP2	0.863	
Perceived Usefulness	PU	PU1	0.827	0.658
		PU2	0.798	
		PU3	0.808	
Perceived Ease of Use	PEOU	PEOU1	0.807	0.655
		PEOU2	0.817	
		PEOU3	0.804	

C. Discriminant Validity

Discriminant validity was assessed using the Fornell-Larcker criterion to confirm that each construct is distinct from others. Table IV shows that the square root of AVE for each construct (highlighted diagonally) is greater than its correlations with other constructs, indicating good discriminant validity. An exception was noted where the square root of AVE for AI Adoption (AIA) was slightly lower than its correlation with Perceived Usefulness (PU), but the difference was minimal and still acceptable.

The HTMT ratio in Table V confirms discriminant validity, as all inter-item correlations are below the 0.90 threshold, indicating that the constructs are distinct. Along with the Fornell-Larcker criterion, this validates the model's constructs, confirming its reliability, validity, and dependability.

Table IV. Discriminant validity- Fornell-Larcker criterion.

	AIA	CO	CP	GI	MS	MU	PEOU	PU	RA	TC	TY	VP
AIA	0.869											
CO	0.297	0.772										
CP	0.455	0.372	0.841									
GI	0.441	0.467	0.641	0.812								
MS	0.43	0.388	0.562	0.567	0.833							
MU	0.462	0.373	0.63	0.694	0.466	0.832						
PEOU	0.625	0.38	0.513	0.571	0.407	0.581	0.809					
PU	0.941	0.297	0.485	0.443	0.461	0.49	0.658	0.811				
RA	0.468	0.343	0.551	0.522	0.562	0.48	0.427	0.504	0.829			
TC	0.327	0.283	0.478	0.532	0.478	0.435	0.41	0.372	0.63	0.802		
TY	0.457	0.329	0.509	0.549	0.67	0.476	0.493	0.493	0.564	0.501	0.843	
VP	0.402	0.354	0.554	0.571	0.393	0.504	0.358	0.448	0.469	0.422	0.477	0.846

Table V. Discriminant Validity Test (HTMT Criteria).

	AIA	CO	CP	GI	MS	MU	PEOU	PU	RA	TC	TY	VP
AIA												
CO	0.367											
CP	0.652	0.578										
GI	0.556	0.675	0.772									
MS	0.535	0.56	0.832	0.745								
MU	0.681	0.626	0.805	0.776	0.71							
PEOU	0.799	0.489	0.777	0.767	0.533	0.802						
PU	0.866	0.373	0.73	0.585	0.604	0.757	0.882					
RA	0.578	0.449	0.816	0.693	0.723	0.727	0.554	0.655				
TC	0.418	0.415	0.72	0.719	0.627	0.681	0.563	0.504	0.825			
TY	0.556	0.494	0.737	0.714	0.855	0.71	0.628	0.633	0.716	0.659		
VP	0.568	0.558	0.934	0.849	0.569	0.869	0.526	0.675	0.693	0.625	0.684	

D. Statistical Result Analysis

Table VI presents the mean and standard deviation of factors influencing AI adoption using the combined TAM and TOE frameworks.

Table VI. Mean and standard deviation for PU & PEOU of AI adoption factors.

Hypothesis	Mean	Standard Deviation
CO → PEOU	0.126	0.068
CO → PU	0.031	0.083
CP → PEOU	0.129	0.096
CP → PU	0.083	0.103
GI → PEOU	0.195	0.116
GI → PU	-0.063	0.116
MS → PEOU	-0.1	0.083
MS → PU	0.094	0.084
MU → PEOU	0.28	0.081
MU → PU	0.204	0.096
PEOU → AIA	0.011	0.037
PU → AIA	0.934	0.025
RA → PEOU	0.017	0.11
RA → PU	0.199	0.093
TC → PEOU	0.062	0.083
TC → PU	-0.031	0.085
TY → PEOU	0.224	0.09
TY → PU	0.158	0.092
VP → PEOU	-0.108	0.09
VP → PU	0.132	0.093

Perceived Usefulness (PU) had the highest mean (0.934) and lowest standard deviation (0.025), indicating strong and consistent influence on AI adoption. Market Uncertainty → PEOU also showed a relatively high mean (0.28), aligning with its significant path coefficient, suggesting it's a key driver of AI adoption.

E. Hypothesis Testing

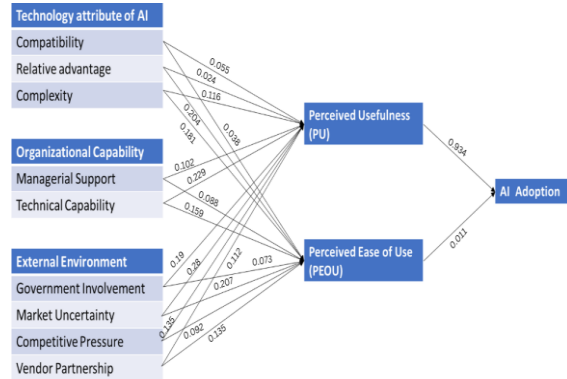


Fig. 3. Result of proposed model.

Conversely, Government Involvement had the lowest mean (-0.063) and the highest standard deviation (0.116), reflecting mixed opinions and minimal contribution to perceived usefulness. Complexity showed the lowest variability (SD = 0.083), indicating general agreement that it has little impact on PU. Moderate deviations in factors like Vendor Partnership and Relative Advantage (SD ≈ 0.093) suggest a fair level of consensus on their roles in influencing PU.

Table VII. Path coefficient of hypothesis.

Effects	Hypothesis	Path Coefficient
Technology Compatibility → PU	H1a	0.055
Technology Compatibility → PEOU	H1b	0.038
Relative Advantage → PU	H2a	0.024
Relative Advantage → PEOU	H2b	0.204
Complexity → PU	H3a	0.116
Complexity → PEOU	H3b	0.181
Managerial Support → PU	H4a	0.102
Managerial Support → PEOU	H4b	0.088
Technical Capability → PU	H5a	0.229
Technical Capability → PEOU	H5b	0.159
Government Involvement → PU	H6a	0.19
Government Involvement → PEOU	H6b	0.073
Market Uncertainty → PU	H7a	0.28
Market Uncertainty → PEOU	H7b	0.207
Competitive Pressure → PU	H8a	0.135
Competitive Pressure → PEOU	H8b	0.092
Vendor Partnership → PU	H9a	0.112
Vendor Partnership → PEOU	H9b	0.135
PU → Adoption of AI	H10a	0.934
PEOU → Adoption of AI	H10b	0.011

The significance of direct relationship was calculated through bootstrap method using 5000 resamples and one-tailed critical t-value exceeding ±1.65. The result of equation modelling as shown in Fig. 3.

Table VII and VIII examines the effects of technological factors on Perceived Usefulness (PU) and Perceived Ease of Use (PEOU).

Table VIII. Analysis of attributes towards AI adoption factors.

Effects	Hypothesis	P values	Significance	Hypothesis
Technology Compatibility -> PU	H1a	0.252	p>0.05	Not supported
Technology Compatibility -> PEOU	H1b	0.329	p>0.05	Not supported
Relative Advantage -> PU	H2a	0.412	p>0.05	Not supported
Relative Advantage -> PEOU	H2b	0.014	p<0.05	Supported
Complexity -> PU	H3a	0.044	p<0.05	Supported
Complexity -> PEOU	H3b	0.029	p>0.05	Supported
Managerial Support -> PU	H4a	0.01	p<0.01	Supported
Managerial Support -> PEOU	H4b	0.034	p<0.05	Supported
Technical Capability -> PU	H5a	0.005	p<0.05	Supported
Technical Capability -> PEOU	H5b	0.042	p<0.05	Supported
Government Involvement -> PU	H6a	0.046	p<0.05	Supported
Government Involvement -> PEOU	H6b	0.264	p>0.05	Not supported
Market Uncertainty -> PU	H7a	0	p<0.05	Supported
Market Uncertainty -> PEOU	H7b	0.015	p<0.05	Supported
Competitive Pressure -> PU	H8a	0.041	p<0.05	Supported
Competitive Pressure -> PEOU	H8b	0.187	p>0.05	Not supported
Vendor Partnership -> PU	H9a	0.035	p<0.05	Supported
Vendor Partnership -> PEOU	H9b	0.031	p<0.05	Supported
PU -> Adoption of AI	H10a	0	p<0.001	Supported
PEOU -> Adoption of AI	H10b	0.379	p>0.05	Not supported

E.1. Technology Attributes

E.1.1. Technology Compatibility (H1a & H1b)

Both hypotheses are unsupported, with non-significant p-values (PU: 0.252, PEOU: 0.329). This suggests that AI's compatibility with existing systems has minimal influence on its perceived value or ease of use in Malaysian telcos, likely due to the assumption that AI will naturally integrate with legacy systems.

E.1.2. Relative Advantage (H2a & H2b)

H2a is rejected (PU: p = 0.412), indicating no significant effect on usefulness. However, H2b is supported (PEOU: p = 0.014), showing that AI's ease of use is positively influenced by perceived benefits, as companies focus more on usability improvements.

E.1.3. Complexity (H3a & H3b)

Both sub-hypotheses are supported (PU: p = 0.044, PEOU: p = 0.029), confirming that higher complexity negatively affects both perceived usefulness and ease of use. This is due to employees potentially feeling overwhelmed by complex AI systems, aligning with prior research.

E.2. Organizational Attributes

E.2.1. Managerial Support (H4a & H4b)

Both hypotheses are supported (PU: p = 0.01, PEOU: p = 0.034). Strong managerial backing enhances employees' perception of AI as useful and easy to use. This support likely includes resource allocation, fostering innovation, and addressing employee concerns, which helps reduce resistance to change during AI adoption.

E.2.2. Technical Capability (H5a & H5b)

Both sub-hypotheses are supported (PU: p = 0.005, PEOU: p = 0.042). A skilled workforce, robust IT infrastructure, and organizational expertise significantly boost PU and PEOU. In Malaysia's telecom sector, technical capability is vital for effectively deploying AI in complex tasks like network optimization and analytics.

E.3. External Environment Attributes

E.3.1. Government Involvement (H6a & H6b)

H6a is supported (PU: p = 0.046), showing that supportive policies and regulations can enhance trust and drive AI adoption.

H6b is not supported (PEOU: p = 0.264), indicating that government involvement doesn't necessarily make AI easier to use, and may even introduce complexity.

E.3.2. Market Uncertainty (H7a & H7b)

Both hypotheses are supported (PU: p = 0.000, PEOU: p = 0.015), suggesting that in unpredictable environments, telecom companies see AI as both useful and easy to use to enhance adaptability, decision-making, and cost-efficiency.

E.3.3. Competitive Pressure (H8a & H8b)

H8a is supported (PU: p = 0.041), showing that competition encourages firms to adopt AI for strategic benefits.

H8b is not supported (PEOU: p = 0.187), as competition does not significantly influence how easy AI systems are perceived to be.

E.3.4. Vendor Partnership (H9a & H9b)

Both hypotheses are supported (PU: p = 0.035, PEOU: p = 0.031). AI vendors provide crucial resources such as training and system integration support, which help employees perceive AI as both useful and user-friendly.

E.4. TAM attribute of AI Adoption Factors

E.4.1. Perceived Usefulness (PU) - AI Adoption (H10a)

H10a is strongly supported (Path Coefficient = 0.934, p < 0.001), confirming that PU is the primary driver of AI adoption. Employees and organizations are more likely to adopt AI when they believe it brings substantial benefits like process automation, decision support, and strategic improvements.

E.4.2. Perceived Ease of Use (PEOU) - AI Adoption (H10b)

H10b is not supported (Path Coefficient = 0.011, p = 0.379), indicating that ease of use does not significantly influence AI adoption. In Malaysia's telecom industry, functional benefits like productivity, cost savings, and customer service are prioritized over usability.

F. Summary of Research Findings

The paper has determined the best practices and essential success factors influencing the adoption of

AI in telecommunications in Malaysia. The various ways in which AI is being used include network optimization, predictive maintenance and customer service. The results of the 165 survey responses analyzed with SPSS and SmartPLS identified four key enablers of adoption, namely, managerial support, technical capability, market uncertainty, and vendor partnerships, which significantly impacted the adoption ($p < 0.01$). Of these, the least considered is perceived ease of use and the best predictor is perceived usefulness (PU) which emphasizes on the fact that employees are more interested in the practical advantage of the AI and are less concerned with ease of use. To speed up AI adoption, it is worth working on the delivery of tangible value, training and technical assistance, leadership buy-in, and strong partnerships with supplier, stakeholders, and regulators to establish an enabling ecosystem.

VI. CONCLUSION

This study examined the use of artificial intelligence (AI) in Malaysia's telecom sector, emphasizing how it can enhance customer satisfaction, operational effectiveness, and reduce human workload. Using both local and international case studies, such as those from Vodafone, Telekom Malaysia, Maxis, and CelcomDigi, the study determined the most effective methods and important factors that facilitate the adoption of AI. The study presented and verified a conceptual framework integrating the Technology-Organization-Environment (TOE) and Technology Acceptance Model (TAM) using data gathered from 165 network department employees and analyzed using SPSS and SmartPLS. The results show that the adoption of AI is strongly influenced by vendor partnerships, market uncertainty, technical capacity, and managerial backing. One key mediating component that emerged was perceived usefulness (PU), which emphasized how crucial it is to show people real benefits. Even though they had little direct impact, technological elements are nonetheless crucial for creating an atmosphere that is favorable for the use of AI. It was discovered that strategic vendor collaboration and organizational leadership were very important for facilitating a successful integration. Notwithstanding these contributions, the study's generalizability may be limited by its very small and narrow sample, which consists of workers from network departments in Malaysian telecoms. Response bias may also be introduced by the self-reported nature of survey data and the lengthy survey time. The study, however, contributes to the increased theoretical knowledge by incorporating TOE and TAM frameworks to reflect the multidimensional factors affecting the adoption of AI in the telecom industry. In practice, it offers industry stakeholders with practical recommendations, advising them to prioritize the level of industry commitment of leaders, preparedness in terms of technology, and involvement of vendors.

VII. FUTURE WORK

Future studies could broaden the scope of this research by incorporating perspectives on AI ethics, trust, and workforce readiness, which are increasingly critical for sustainable AI adoption. Ethical considerations such as data privacy, transparency, and algorithmic fairness play a vital role in shaping public confidence and organizational accountability. Moreover, workforce readiness and trust in AI technologies significantly influence how employees perceive and engage with AI-driven systems. Integrating these ethical and human-centric dimensions into future models would provide a more comprehensive understanding of AI adoption beyond technical and organizational determinants. This study may also be extended further in the future to provide a better understanding of AI adoption behavior in other industries, the influence of cultural factors, a larger and more diverse sample size, and long-term organizational impacts. Expanding the analysis in these directions would enhance the generalizability and practical relevance of AI adoption research within and beyond the telecommunications sector.

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AUTHOR CONTRIBUTIONS

Suvitha Palani: Research Design, Data Collection, Data Analysis, Implementation, Visualization, and Drafting of the Manuscript.

Siva Priya Thiagarajah: Conceptualization, Main Supervision, Methodological Guidance, Validation, Critical Review, and Final Approval of the Manuscript.

Farzana Sharmin Nila: Investigation Support, Manuscript Review and Editing, and Final Draft Preparation.

CONFLICT OF INTERESTS

No conflict of interests was disclosed.

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Our publication ethics follow The Committee of Publication Ethics (COPE) guideline. <https://publicationethics.org/>

REFERENCES

- [1] U. B. Mir, S. Sharma, A. K. Kar and M. P. Gupta, "Critical success Factors for Integrating Artificial Intelligence and Robotics," *Digit. Policy, Regul. Gov.*, vol. 22, no. 4, 307-331, 2020, doi: 10.1108/DPRG-03-2020-0032.
- [2] S. N. Sekaran and M. R. Basir Khan, "Transforming Telecommunications Infrastructure in Malaysia: The Role of AI in Network Deployment and Optimization," *Malaysian J. Business, Econ. Manag.*, vol. 3, no. 2, pp. 174-182, 2024.
- [3] E. Lim WeiLee, R. Sham, A. Loi, E. Shion and B. Wong, "M-Commerce Adoption Among Youths in Malaysia: Dataset Article," *Data Br.*, vol. 42, pp. 108238, 2022.
- [4] "Maxis Integrated Annual Report 2023," Maxis Limited,

- 2023.
- [5] "Special Report: Charting A Cohesive National Strategy for AI - Infra Mobile Digital" [Available Online on 28 June 2025.] https://inframobiledigital.com/special-report-charting-a-cohesive-national-strategy-for-ai/?utm_source=chatgpt.com.
 - [6] S. Lada *et al.*, "Determining Factors Related to Artificial Intelligence (AI) Adoption Among Malaysia's Small and Medium-Sized Businesses," *J. Open Innov. Technol. Mark. Complex.*, vol. 9, no. 4, pp. 100144, 2023.
 - [7] H. Choung, P. David and A. Ross, "Trust in AI and Its Role in the Acceptance of AI Technologies," *Int. J. Hum. Comput. Interact.*, vol. 39, no. 9, pp. 1727–1739, 2023.
 - [8] A. T. Mazikana, "The impact of Customer Relationship Management on Customer Satisfaction in Telecommunication Industry in Zimbabwe," *SSRN Electron. J.*, pp. 13–52, 2023..
 - [9] "Malaysia's Blueprint for AI Dominance in ASEAN - Telecom Review Asia." [Available online 28 June 2025.] https://www.telecomreviewasia.com/news/interviews/4791-malaysia-s-blueprint-for-ai-dominance-in-asean/?utm_source=chatgpt.com.
 - [10] T. Davenport and R. Kalakota, "The Potential for Artificial Intelligence in Healthcare," *Futur. Healthc. J.*, vol. 6, no. 2, pp. 94–98, 2019.
 - [11] Q. Guo and W. Huang, "Analyzing the Diffusion of Innovations Theory," *Sci. Soc. Res.*, vol. 6, pp. 95–98, 2024.
 - [12] R. Pelánek, T. Effenberger, and J. Čechák, "Complexity and Difficulty of Items in Learning Systems," *Int. J. Artif. Intell. Educ.*, vol. 32, no. 1, pp. 196–232, 2022.
 - [13] H. Chen, "Success Factors Impacting Artificial Intelligence Adoption: Perspective from the Telecom Industry in China," *PhD Thesis*, Old Dominion University, pp. 192, 2019.
 - [14] P. Mikalef and M. Gupta, "Artificial Intelligence Capability: Conceptualization, Measurement Calibration, and Empirical Study on Its Impact on Organizational Creativity and Firm Performance," *Inf. Manag.*, vol. 58, no. 3, pp. 103434, 2021.
 - [15] T. Sever and G. Contissa, "Automated Driving Regulations – Where Are We Now?" *Transp. Res. Interdiscip. Perspect.*, vol. 24, pp. 101033, 2024.
 - [16] S. Chatterjee, N. P. Rana, Y. K. Dwivedi and A. M. Baabdullah, "Understanding AI Adoption in Manufacturing and Production Firms using An Integrated TAM-TOE Model," *Technol. Forecast. Soc. Change*, vol. 170, pp. 120880, 2021.