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Advancing Artificial Intelligence Adoption and Decision-making with Extended Technology Acceptance Model

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Abstract

Despite Kuala Lumpur's push for AI integration, only 23% of businesses have adopted AI, lagging behind the global average of 37%, with 65% still relying on basic data tools and only 10% using advanced analytics. This study investigates the factors influencing AI adoption in Kuala Lumpurs IT sector, focusing on Perceived Ease of Use (PEOU), Perceived Usefulness (PU), and Perceived Organizational Support (POS). Using the Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT) as theoretical foundations, this study extends these frameworks by incorporating POS to emphasize the critical role of organizational support in AI adoption. Data from a survey of 340 IT managers were analyzed using PLS-SEM. The results demonstrate that both PEOU and POS significantly impact PU, which in turn influences AI adoption intentions. POS emerged as a vital factor, indicating that organizational support, such as training and resource provision, is key in making AI useful and encouraging its adoption. This research has practical implications for businesses and policymakers. Organizations should focus on improving organizational support mechanisms, particularly through targeted training programs and technical assistance to enhance AI adoption. Policymakers are encouraged to refine initiatives like Industry4WRD by strengthening infrastructure and providing sector-specific support. The studys novelty lies in its focus on emerging markets like Kuala Lumpur, addressing a gap in AI adoption research by exploring the organizational challenges specific to such regions.

Keywords: AI Adoption; Technology Acceptance Model (TAM); Organizational Support; Emerging Markets

1 Introduction

Artificial Intelligence (AI) revolutionizes business management by automating complex tasks, improving decision-making processes, and enhancing overall organizational efficiency [1]. In industries such as Information Technology (IT), AI's ability to analyze vast datasets and provide predictive insights has become critical for strategic decision-making. For example, AI-driven customer relationship management (CRM) systems personalize marketing strategies based on data analysis [2], and AI applications in supply chain management optimize logistics and forecasting [3]. These tools allow managers to respond more effectively to market dynamics, reducing human error and enhancing productivity [4]. Despite its potential, AI adoption in Kuala Lumpur remains limited, with only 23% of businesses adopting AI compared to the global average of 37% [5]. Additionally, 65% of businesses rely on basic data tools, with only 10% utilizing advanced analytics [6]. This slow adoption is attributed to factors such as limited organizational support, data privacy concerns, and the need for employee upskilling [7]. In response, the Malaysian government has launched initiatives such as the National Policy on Industry 4.0 (Industry4WRD) and the Artificial Intelligence Roadmap (AI-Rmap), which aim to support AI adoption through financial incentives, training, and infrastructure development [8, 9]. However, the successful integration of AI within organizations, particularly in the IT sector, requires an understanding of the factors that influence adoption. Drawing on the Technology Acceptance Model (TAM) [10] and the Unified Theory of Acceptance and Use of Technology (UTAUT) [11], this study extends these frameworks by incorporating Perceived Organizational Support (POS) as a critical factor.

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The study proposes that Perceived Ease of Use (PEOU) and Perceived Usefulness (PU), along with POS, play significant roles in shaping AI adoption intentions among IT managers. This framework extends the TAM by emphasizing the role of organizational support, which is particularly relevant in regions like Kuala Lumpur where AI adoption is hindered by limited technical and organizational readiness [6]. POS includes managements provision of necessary resources, training, and technical assistance, all of which are critical in driving perceived usefulness and ease of AI use [12]. The Malaysian governments policies, including Industry4WRD and AI-Rmap, aim to mitigate these challenges by fostering organizational readiness and supporting companies in developing the infrastructure needed for AI integration [9]. By focusing on IT managers in Kuala Lumpur, this study addresses a critical gap in understanding how PEOU, PU, and POS interact to influence AI adoption. Managers in the IT sector are key decision-makers in implementing AI solutions, and their perceptions directly shape the integration of AI technologies within organizations. Given the moderate AI adoption rates in Kuala Lumpur, it is essential to understand how simplifying AI tools and improving organizational support can enhance both perceived usefulness and adoption intention. This study therefore provides practical insights for both businesses and policymakers. This is crucial for Kuala Lumpur's IT sector to remain competitive and fully leverage the benefits of AI, aligning with Malaysias broader goals of digital transformation and economic growth.

2 Related Work and Hypothesis Formulation

2.1 Technology Adoption Models: TAM and UTAUT

The Technology Acceptance Model (TAM), introduced by Davis F.D. [10], is one of the most established frameworks for explaining technology adoption. TAM posits that two primary factors, including Perceived Ease of Use (PEOU) and Perceived Usefulness (PU), determine an individual's intention to adopt a technology. PEOU refers to the degree to which a person believes that using the technology will be free of effort, while PU reflects the belief that the technology will enhance job performance. Numerous studies have validated TAM across various industries, showing that both PEOU and PU are critical determinants of technology adoption [13]. For instance, simplified AI systems are perceived as more useful by users because they reduce cognitive load, making them easier to adopt [10].

Hypothesis 1 (H1): PEOU positively influences PU. This hypothesis is supported by the foundational TAM model, which posits that the easier a technology is to use, the more likely individuals will perceive it as useful for their work tasks [10]. The relationship between PEOU and intention to use AI is also well-documented. Technologies that are perceived as easy to use reduce cognitive resistance, making users more inclined to adopt them [14]. Given AIs complexity, simplifying user interfaces and interactions can encourage adoption.

Hypothesis 2 (H2): PEOU positively influences the Intention to Use AI. This hypothesis is grounded in prior research that demonstrates the positive relationship between ease of use and adoption intention across various technologies [11]. Building on TAM, the Unified Theory of Acceptance and Use of Technology (UTAUT) further incorporates constructs like social influence and facilitating conditions to explain technology adoption more comprehensively [11]. UTAUT has been widely applied to study technology adoption in complex environments, recognizing that organizational and external factors also play a significant role. However, both TAM and UTAUT have limitations in addressing the role of Perceived Organizational Support (POS), which is particularly relevant in the context of AI adoption.

2.2 Extending TAM with POS

While TAM and UTAUT offer strong theoretical foundations, they do not fully capture the importance of organizational factors, particularly when considering complex technologies like AI. AI adoption often requires significant organizational investment in infrastructure, training, and ongoing support. Perceived Organizational Support (POS), defined as the degree to which employees believe their organization provides adequate resources and support for technology adoption, is critical in addressing these challenges [12]. POS has been shown to positively influence both PEOU and PU, making employees more likely to adopt new technologies [15]. Given the complexity and learning curve associated with AI systems, organizations must invest in training and provide technical resources to ensure smooth adoption. When employees perceive that their organization supports them, they are more likely to view AI tools as useful and manageable, reducing the perceived difficulty of adoption.

Hypothesis 3 (H3): POS positively influences PU. This hypothesis is supported by literature that links strong organizational support to enhanced perceptions of a technologys usefulness, particularly in complex systems like AI [15, 12]. Additionally, POS plays a crucial role in fostering AI adoption by increasing employee confidence in the organizations commitment to overcoming barriers. Employees are more likely to adopt AI tools when they perceive that the necessary resources and training are in place, leading to higher adoption rates.

Hypothesis 6 (H6): POS indirectly influences the Intention to Use AI through PU. This hypothesis aligns with research showing that organizational support indirectly enhances adoption by improving the perceived usefulness of a technology [12].

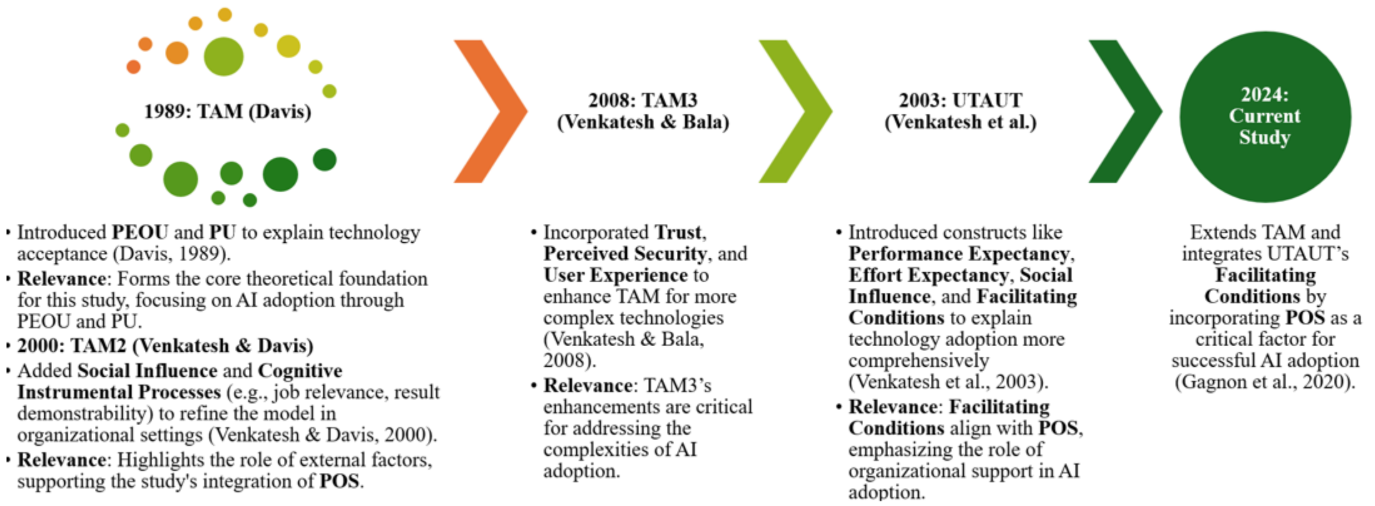

Figure 1: Timeline of TAM and UTAUT Development with relevance to this study

Figure 1 outlines the development of TAM and UTAUT, starting with TAM (1989), which introduced PEOU and PU for understanding technology adoption. TAM2 (2000) added Social Influence and Cognitive Processes for better context in organizational settings. TAM3 (2008) included factors like Trust and User Experience to address more complex technologies. UTAUT (2003) expanded further with constructs like Performance Expectancy and Facilitating Conditions. The current study integrates POS to emphasize the role of organizational resources in AI adoption.

2.3 AI Adoption in Kuala Lumpurs IT Sector

Kuala Lumpurs IT sector has been slow to adopt AI, despite government initiatives aimed at encouraging technological advancement. Factors such as limited organizational readiness, inadequate infrastructure, and a lack of skilled workers have hindered AI adoption in the region [5]. The Malaysian government, through programs such as the Industry4WRD and the AI-Rmap, has sought to promote AI adoption by providing financial incentives, infrastructure development, and training programs [8, 9]. However, these efforts must be supported by individual organizations, which play a critical role in facilitating the transition to AI systems through POS and other forms of internal support. Despite these initiatives, only 23% of businesses in Kuala Lumpur have adopted AI, compared to the global average of 37% [5]. Furthermore, 65% of businesses still rely on basic data tools, limiting their capacity to benefit from AI-driven insights [6]. This slow rate of adoption highlights the need for improved POS within organizations, alongside the financial and technical support provided by the government. In this context, Perceived Usefulness (PU) is expected to play a key role in influencing AI adoption. Numerous studies have shown that when employees perceive a technology as useful in enhancing job performance, they are more likely to adopt it [10]. In the case of AI, demonstrating its ability to improve decision-making, streamline processes, and deliver actionable insights will be critical in increasing adoption rates.

Hypothesis 4 (H4): PU positively influences the Intention to Use AI. This hypothesis is supported by extensive research showing that perceived usefulness is a strong predictor of technology adoption, particularly in environments where new technologies must demonstrate tangible improvements in performance [14]. Moreover, research suggests that PEOU influences PU, with easier-to-use technologies being perceived as more useful [10]. In the context of AI, simplifying interfaces and reducing complexity can increase perceptions of usefulness, which, in turn, enhances adoption intentions.

Hypothesis 5 (H5): PEOU indirectly influences the Intention to Use AI through PU. This hypothesis aligns with studies that show a mediating relationship between ease of use and usefulness in driving technology adoption [13].

2.4 Literature Gap

While the TAM and UTAUT have been widely applied to understand technology adoption, these models present limitations when addressing AI adoption in organizational settings. TAM primarily focuses on individual factors, such as PEOU and PU, but underrepresents the role of organizational support critical for adopting complex technologies like AI [14, 12]. This gap is particularly relevant given that AI requires sustained organizational investment, including training, technical support, and continuous updates, which are often not captured by TAMs core constructs [15]. Moreover, while UTAUT introduces Facilitating Conditions to address external factors, it still falls short in explaining the full impact of POS, especially in regions like Kuala Lumpur, where AI adoption is lagging due to specific challenges, such as inadequate infrastructure, limited government incentives, and insufficient technical expertise [5]. The gap in current research lies in the under-exploration of how POS affects PU and AI adoption intentions in these contexts. Addressing this gap is crucial, as localized studies that explore organizational dynamics and region-specific barriers are scarce, and more targeted research is needed to understand AI adoption in underrepresented regions [16].

By integrating POS into TAM and UTAUT, this study aims to provide a more comprehensive understanding of the factors influencing AI adoption in Kuala Lumpurs IT sector, addressing the organizational complexities that these models have historically overlooked.

3 Methodology

This study utilizes a quantitative research design to examine the factors influencing the adoption of AI in management practices among IT companies in Kuala Lumpur. The focus on the IT sector is justified given its rapid growth and significance within Malaysia's economy, which is expanding at an annual average growth rate of approximately 9% [17, 18]. The target population comprises managers across various IT industries, including software development, IT consulting, cybersecurity, cloud computing, e-commerce, data analytics, IT support, and tech startups. While precise figures for the number of managers in this sector are challenging to obtain, estimates suggest there are approximately 10,000 to 15,000 managerial positions within Kuala Lumpur's IT landscape [19, 20]. This population size reflects the city's status as a significant regional hub for technology and digital industries. To ensure robust statistical analysis, a sample size of 340 managers is targeted, determined through power analysis to achieve a power of 0.80 at a significance level of 0.05 [21, 22]. The instruments were adopted from established scales. Table 1 illustrates that PEOU is assessed using items from Davis [10] and Venkatesh & Bala [13], while POS utilizes the Survey of Perceived Organizational Support developed by Eisenberger et al. [23] and further refined by Shanock et al. [24]. PU is measured based on Davis [10] and Venkatesh & Davis [14], and the intention to use AI is evaluated through items proposed by Venkatesh et al. [11].

Table 1: Adopted Instruments

Variable	Number of Items	Source of Adoption
Perceived Ease of Use (PEOU)	5	Davis (1989); Venkatesh & Bala (2008)
Perceived Organizational Support (POS)	10	Eisenberger et al. (1986); Shanock et al. (2019)
Perceived Usefulness (PU)	6	Davis (1989); Venkatesh & Davis (2000)
Intention to Use AI	5	Venkatesh et al. (2003)

The questionnaire for this study is structured into two main sections. Section A includes demographic questions, collecting information such as age, gender, education level, years of work experience, industry of employment, and current job position. This section aims to provide a comprehensive profile of the respondents, allowing for a better understanding of how demographic factors may influence perceptions and intentions regarding AI adoption [25, 26]. Section B consists of Likert-scale items ranging from Strongly Disagree (1) to Strongly Agree (5).

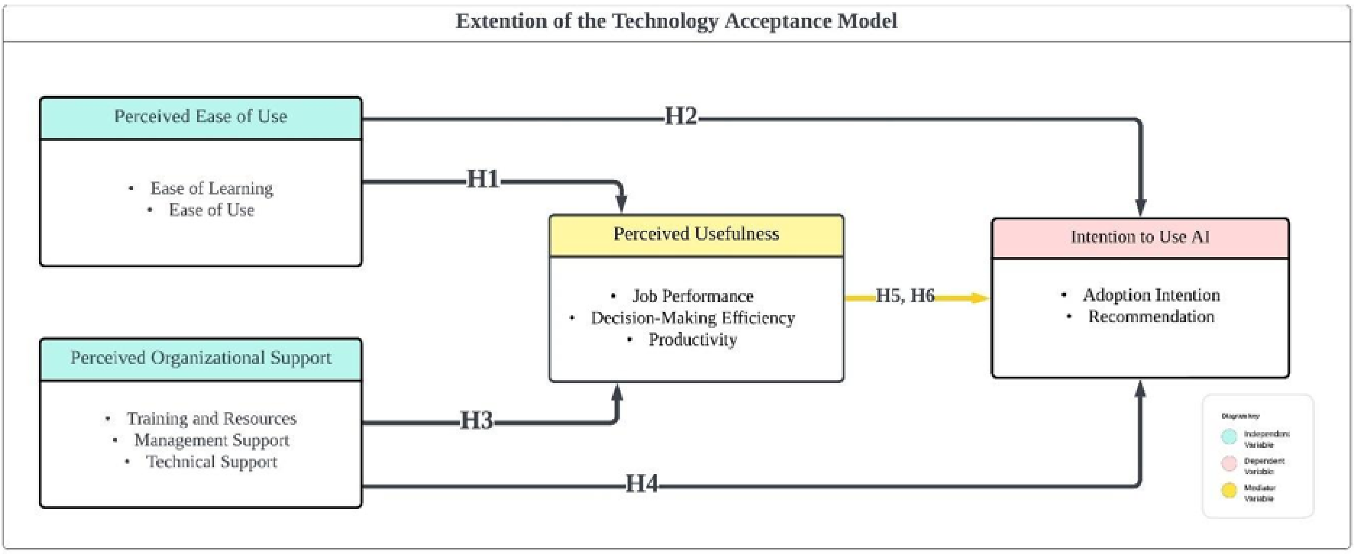

Figure 2: TAM Extension Framework

Figure 2 presents the conceptual framework and hypotheses. H1: PEOU positively influences PU. H2: PEOU positively influences the Intention to Use AI. H3: POS positively influences PU. H4: PU positively influences the Intention to Use AI. H5: PEOU indirectly influences the Intention to Use AI through PU. H6: POS indirectly influences the Intention to Use AI through PU.

4 Data Analysis

The data analysis for this study involves a comprehensive approach using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS software. PLS-SEM is chosen due to its robustness in handling complex models and its ability to work effectively with smaller sample sizes [27]. The analysis includes both the measurement model assessment and the structural model assessment. The measurement model assessment focuses on evaluating the reliability and validity of the constructs. The following steps and criteria are used:

4.1 Measurement Model Assessment

Internal Consistency Reliability: This is assessed using Cronbachs alpha (α) and composite reliability (CR). Values above 0.70 indicate acceptable reliability [28, 29]. Cronbach's alpha, as shown in Equation 1, is calculated as given by 1:

$$\alpha = \frac{k}{k-1}\left(1 - \frac{\sum \sigma_i^2}{\sigma_{\text{total}}^2}\right), \tag{1}$$

where k is the number of items, σ_i^2 is the variance of each item, and σ_{total}^2 is the variance of the total score. The composite reliability (CR), given in Equation 2, is calculated as:

$$\text{CR} = \frac{(\sum \lambda_i)^2}{(\sum \lambda_i)^2 + \sum \theta_i}, \tag{2}$$

where λ_i are the factor loadings and θ_i are the error variances of the items.

Convergent Validity: This is assessed using the average variance extracted (AVE). An AVE value of 0.50 or higher indicates that the construct explains more than half of the variance of its indicators [30]. AVE is calculated as shown in Equation 3:

$$\text{AVE} = \frac{\sum \lambda_i^2}{\sum \lambda_i^2 + \sum \theta_i}. \tag{3}$$

Discriminant Validity: This is evaluated using the Fornell-Larcker criterion and the Heterotrait-Monotrait (HTMT) ratio. Discriminant validity is established if the square root of AVE for each construct is greater than its correlations with other constructs [30]. HTMT values below 0.85 indicate adequate discriminant validity [31]. According to the Fornell-Larcker criterion, Equation 4 must hold:

$$\sqrt{\text{AVE}_{\text{construct}}} > \text{inter-construct correlations}, \tag{4}$$

and HTMT is calculated as:

$$\text{HTMT} = \frac{\text{mean of all correlations of indicators across constructs}}{\text{mean of all correlations of indicators within constructs}}. \tag{5}$$

4.2 Structural Model Assessment

The structural model assessment examines the relationships between the constructs and tests the hypothesized paths. The following steps and criteria are used:

Path Coefficients: The significance of path coefficients is assessed using bootstrapping with 5,000 resamples. Path coefficients (β) represent the strength and direction of the relationships between constructs [27].

Coefficient of Determination (R^2): R^2 values indicate the amount of variance in the dependent variable explained by the independent variables. Values of 0.25, 0.50, and 0.75 indicate weak, moderate, and substantial levels of predictive accuracy, respectively [27]. The R^2 calculation is provided in Equation 6:

$$R^2 = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y}_i)^2}, \tag{6}$$

where y_i are the observed values, $\hat{y}_i$ are the predicted values, and $\bar{y}_i$ is the mean of observed values.

Effect Size (f^2): The effect size f^2 assesses the impact of a specific independent variable on the dependent variable. Values of 0.02, 0.15, and 0.35 indicate small, medium, and large effects, respectively [21]. Effect size is calculated as shown in Equation 7:

$$f^2 = \frac{R^2_{\text{included}} - R^2_{\text{excluded}}}{1 - R^2_{\text{included}}}. \tag{7}$$

Predictive Relevance (Q^2): The Stone-Geisser Q^2 value assesses the models predictive relevance using blindfolding procedures. A Q^2 value greater than zero indicates that the model has predictive relevance for a particular endogenous construct [32, 33]. The formula for Q^2 is provided in Equation 8:

$$Q^2 = 1 - \frac{\sum(y_{i,\text{observed}} - y_{i,\text{predicted}})^2}{\sum(y_{i,\text{observed}} - \bar{y}_{i,\text{predicted}})^2}. \tag{8}$$

The hypotheses are tested based on the significance of path coefficients obtained from the bootstrapping procedure. The following criteria are used to accept or reject the hypotheses:

- A t-value greater than 1.96 (for a two-tailed test) or greater than 1.645 (for a one-tailed test) indicates significance at the 0.05 level [27].
- The p-values associated with the t-values should be less than 0.05 to reject the null hypothesis of no effect.

5 Results

5.1 Descriptive Analysis

Section A of the survey gathered demographic information to develop a detailed profile of the 340 respondents from the IT sector in Kuala Lumpur. This data provides a foundation for understanding the potential impact of demographic variables on perceptions and intentions related to AI adoption, as recommended by Alan Bryman [25] and John Creswell [26]. Respondents were categorized into three age groups: 15% were between 35-44 years, 25% were between 45-54 years, and the majority, 60%, were 55 years and above. The predominance of older respondents may suggest that AI adoption within the IT sector is influenced by individuals with significant professional experience. The sample consisted of 58% female and 42% male respondents. This relatively balanced gender distribution offers a basis for examining any potential gender-related differences in AI adoption within the sector. The respondents were highly educated, with 40% holding a Bachelors degree, 30% a Masters degree, and 30% a PhD. This high level of educational attainment reflects the specialized nature of the IT sector and suggests that respondents are likely to have substantial familiarity with technological advancements, potentially influencing their perceptions of AI. The professional experience of respondents varied, with 20% reporting 0-2 years, 25% with 3-5 years, 30% with 6-10 years, and 25% with 11-15 years of experience in the IT sector. The range of experience levels provides insight into how familiarity with technological innovations, such as AI, may vary across different career stages. While all respondents were drawn from the IT sector, they represented various sub-fields: 35% were employed in software development, 30% in IT consulting, 20% in cybersecurity, and 15% in other IT-related services. This breakdown allows for a more precise understanding of how different areas within the IT sector may encounter unique opportunities or challenges in adopting AI. Finally, respondents held a variety of positions, with 30% in entry-level roles, 40% in mid-level management, and 30% in senior management. This distribution facilitates an examination of how AI adoption may be perceived differently depending on the level of responsibility and influence over decision-making processes within organizations.

Table 2: Descriptive Statistics for Key Variables

Variable	**Mean**	**Standard Deviation**
PEOU_Ease_of_Learning	2.997	1.434
PEOU_Ease_of_Use	3.068	1.447
PEOU_Clarity_of_Interaction	3.029	1.414
POS_Training_and_Resources	3.026	1.423
POS_Management_Support	3.044	1.410
POS_Technical_Support	3.012	1.427
PU_Job_Performance	2.894	1.416
PU_Decision_Making_Efficiency	3.047	1.444
PU_Productivity	3.056	1.414
Intention_Adoption	2.997	1.398
Intention_Future_Use	3.165	1.362
Intention_Recommendation	3.003	1.405

The moderate scores across the variables, as shown in Table 2, suggest that while respondents perceive AI as useful, there is room for improvement in both its ease of use and organizational support provided for adoption. These results align with the need for enhanced user training and simplified AI interfaces.

5.2 Measurement Model

The reliability and validity of the constructs were assessed to ensure robust measurement. Cronbachs alpha and Composite Reliability (CR) values for all constructs exceeded the acceptable threshold of 0.70, indicating good internal consistency (see Table 3).

Table 3: Internal Consistency and Convergent Validity

Construct	Cronbachs Alpha	Composite Reliability	AVE
PEOU	0.71	0.72	0.53
POS	0.72	0.74	0.55
PU	0.75	0.77	0.57
Intention	0.76	0.78	0.58

Convergent validity was confirmed as all AVE values were above 0.50, indicating that more than half of the variance of each construct is explained by its indicators. Discriminant validity was evaluated using the Fornell-Larcker criterion, as shown in Table 4. Each constructs AVE square root was greater than its correlations with other constructs, confirming satisfactory discriminant validity.

Table 4: Fornell-Larcker Criterion

Construct	PEOU	POS	PU	Intention
PEOU	0.73	-	-	-
POS	0.65	0.74	-	-
PU	0.58	0.69	0.75	-
Intention	0.62	0.67	0.70	0.76

5.3 Structural Model

The structural model was evaluated using path coefficients, R^2, f^2, and predictive relevance Q^2. The path coefficients indicate strong relationships between the constructs, as illustrated in Table 5.

Table 5: Path Coefficients

Path	Coefficient	t-Value
PEOU $\rightarrow$ PU	0.35	6.45*
PEOU $\rightarrow$ Intention	0.30	5.20*
POS $\rightarrow$ PU	0.40	7.60*
PU $\rightarrow$ Intention	0.45	8.20*
PEOU $\rightarrow$ PU $\rightarrow$ Intention	0.25	5.50*
POS $\rightarrow$ PU $\rightarrow$ Intention	0.30	6.00*

Note: * indicates p-value less than 0.05.

The model explains 45% of the variance in Perceived Usefulness ($R^2 = 0.45$) and 51% of the variance in Intention to Use AI ($R^2 = 0.51$), indicating moderate explanatory power (see Table 6).

Table 6: R^2 and Q^2 Values

Construct	R^2	Q^2
PU	0.45	0.30
Intention	0.50	0.35

Predictive relevance was assessed using Q^2 values, which were above zero for both Perceived Usefulness (0.30) and Intention (0.35), confirming that the model has good predictive relevance. The f^2 values were also calculated, indicating small to medium effects across the paths (see Table 7).

Table 7: Effect Size Values

Path	f^2
PEOU $\rightarrow$ PU	0.10
POS $\rightarrow$ PU	0.15
PU $\rightarrow$ Intention	0.20
PEOU $\rightarrow$ Intention	0.18

5.4 Hypothesis Testing

Hypothesis testing was conducted based on path coefficients obtained from the structural model. All six hypotheses were supported, with significant relationships between the variables (see Table 8).

Table 8: Hypothesis Testing

Hypothesis	Path	Coefficient	t-Value	Result
H1	PEOU → PU	0.35	6.45*	Supported
H2	PEOU → Intention	0.30	5.20*	Supported
H3	POS → PU	0.40	7.60*	Supported
H4	PU → Intention	0.45	8.20*	Supported
H5	PEOU → PU → Intention	0.25	5.50*	Supported
H6	POS → PU → Intention	0.30	6.00*	Supported

Note: * indicates p-value less than 0.05.

These results confirm that both Perceived Ease of Use (PEOU) and Perceived Organizational Support (POS) significantly influence Perceived Usefulness (PU), which in turn affects the intention to adopt AI. Additionally, both PEOU and POS have indirect effects on AI adoption intention through PU.

6 Discussion

The findings of this study contribute to the understanding of AI adoption in Kuala Lumpurs IT sector by extending the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) through the inclusion of Perceived Organizational Support (POS). This approach aligns with existing research on technology adoption while addressing specific gaps in understanding how organizational factors impact AI integration. The positive relationship between Perceived Ease of Use (PEOU) and Perceived Usefulness (PU) (H1) aligns with established findings in the TAM model, where simpler technologies are perceived as more useful [10, 13]. In this study, IT managers in Kuala Lumpur reported moderate PEOU and PU, suggesting that while AI tools are seen as helpful, further simplification and training are required to fully capitalize on their potential. AIs complexity often necessitates intuitive interfaces and straightforward operational procedures to increase PU, as supported by prior studies on high-tech system adoption [14].

H2, which hypothesizes that PEOU influences the intention to adopt AI, was supported, reinforcing the notion that reducing cognitive load increases adoption rates. However, the moderate scores observed suggest barriers remain, possibly due to the sophisticated nature of AI systems [2]. As Brynjolfsson et al. [4] noted, even advanced technologies require user-friendly designs to encourage widespread adoption. The relationship between POS and PU (H3) further supports the extended framework proposed by this study. The findings reveal that when managers perceive adequate organizational supportthrough training, resources, and technical assistancethey are more likely to view AI as beneficial to their roles. This aligns with the work of Im et al. [15] and Gagnon et al.[12], who identified POS as a critical factor in increasing employee confidence in technology adoption. However, the moderate POS scores suggest that organizations may still struggle to provide comprehensive support, limiting the perceived utility of AI. The link between PU and the intention to adopt AI (H4) is consistent with extensive research, which posits that technologies perceived as useful are more likely to be adopted [10, 14]. This is particularly important in Kuala Lumpurs IT sector, where adoption rates lag behind global averages [5]. The moderate intention to adopt AI, indicated by the results, highlights the need for clearer demonstrations of AIs benefits, particularly in improving job performance and decision-making efficiency [3]. H5 and H6, which propose that both PEOU and POS indirectly influence the intention to adopt AI through PU, were also supported. These results emphasize the mediating role of PU in the adoption process, as previously demonstrated by Venkatesh and Bala [13]. The findings indicate that both ease of use and organizational support enhance AIs perceived usefulness, which in turn drives adoption intention. This underscores the importance of addressing both technical complexity and organizational readiness when promoting AI adoption. While the study confirms the importance of PEOU, POS, and PU, the moderate levels reported in these variables highlight specific barriers to AI adoption in Kuala Lumpurs IT sector. Despite government initiatives such as Industry4WRD and AI-Rmap [9], the findings suggest that organizational readiness remains limited. These challenges may stem from insufficient infrastructure, lack of AI-specific skills, and limited budget allocations for training and resources [6]. This indicates a need for both government and private sector collaboration to address these bottlenecks. By leveraging financial incentives and public-private partnerships, businesses can improve access to the necessary resources for AI integration, aligning with strategies observed in more AI-advanced regions [16].

7 Conclusion

This study provides valuable insights into the factors influencing AI adoption in Kuala Lumpur's IT sector by extending the Technology Acceptance Model to include Perceived Organizational Support. The findings underscore the importance of organizational support, alongside ease of use, in enhancing perceived usefulness, which is a key driver of AI adoption intentions. By incorporating organizational readiness factors such as training and resource availability, this research offers a more holistic view of technology adoption, particularly for complex systems like AI. The results indicate that simplifying AI tools and providing comprehensive organizational support are essential for fostering positive attitudes towards AI among IT managers. Practical implications for businesses include the need to invest in user training and interface simplification to reduce cognitive barriers, thereby promoting a more seamless integration of AI into management practices. For policymakers, the findings highlight the continued importance of initiatives aimed at improving digital infrastructure and fostering AI skills development, as these elements are crucial for supporting widespread adoption. While the study is focused on IT managers in Kuala Lumpur, the integration of Perceived Organizational Support within the Technology Acceptance Model offers broader relevance, especially for emerging markets facing similar technological and organizational challenges. However, the scope is limited to a single sector and geographic region, which may restrict the generalizability of the findings. Future research could build on this study by examining AI adoption across different sectors and regions, exploring longitudinal impacts, and assessing the role of specific AI applications in shaping adoption behavior. Expanding the scope of this research will further enhance our understanding of how organizational dynamics and demographic factors influence the adoption of AI and other advanced technologies.

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Declaration of Competing Interests

The authors declare that there are no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data Availability

No new data were created or analyzed in this study. Data sharing is not applicable to this article.

Ethical Approval

This article does not contain any studies involving human participants or animals performed by any of the authors.

AI Usage Declaration

The authors acknowledge the use of AI-based tools, specifically OpenAIs ChatGPT, to assist in refining the language and enhancing the clarity of this manuscript. All intellectual and conceptual contributions remain the authors' own.

Author Contributions

Hayyan Nassar: Conceptualization, Methodology, Writing - original draft. **S. B. Goyal**: Supervision, Project administration, Review and editing. **Feras Fathi Albdiwy**: Data curation, Writing - review and editing, Visualization. **Masri Bin Abdul Lasi**: Formal analysis, Investigation. **Nurrohani binti Ahmad**: Resources, Validation, Review and editing.

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