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Factors Influencing Artificial Intelligence Adoption among Employees in Malaysia's Private Sector

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Abstract

The adoption of Artificial Intelligence (AI) in the private sector is increasingly transforming workplace practices, necessitating an understanding of the factors influencing its acceptance and usage among employees. This study explores the relationships between key determinants, performance expectancy, effort expectancy, social influence, and facilitating conditions and their impact on the actual use of AI, mediated by behavioral intention. Guided by the Unified Theory of Acceptance and Use of Technology (UTAUT), this study utilizes a quantitative approach to collect and analyze data from employees in Malaysia's private sector. The findings reveal that performance expectancy, effort expectancy, social influence, and facilitating conditions significantly influence behavioral intention, which, in turn, mediates their effects on actual AI usage. Facilitating conditions also directly affect actual use, highlighting the importance of organizational support in fostering adoption. The study provides critical insights for private-sector organizations, policymakers, and practitioners aiming to enhance AI acceptance and integration in workplace environments. These results contribute to the existing literature by offering a holistic understanding of the factors driving AI adoption and use, with practical implications for improving workforce readiness and technological implementation strategies.

Keywords: Performance Expectancy, Effort Expectancy; Social Influence, Facilitating Conditions, Behavioural Intention, Actual Use, Artificial Intelligence

Introduction

The adoption and integration of Artificial Intelligence (AI) technologies have significantly transformed how organizations in the private sector manage essential functions such as recruitment, training, performance evaluation, and employee engagement. AI's ability to automate repetitive tasks, enhance decision-making, and improve operational efficiency positions it as a powerful tool for workforce management (Budhwar et al., 2023; Chatterjee & Bhattacharjee, 2020). Despite its potential, the successful implementation of AI depends on several factors influencing individuals' intention and actual use of these technologies. In Malaysia, where AI adoption in the private sector workforce is still in its early stages, understanding these determinants is essential.

This study draws on the Unified Theory of Acceptance and Use of Technology (UTAUT) to explore four key independent variables (IVs) that predict AI adoption: performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2003; Venkatesh, Chan, et al., 2012). These factors are crucial in shaping behavioral intention, which, in turn, mediates the actual use of AI technologies. Performance expectancy, defined as the degree to which individuals believe that using AI will improve their job performance, is a major driver of adoption. Employees are more likely to adopt AI when they recognize its potential to enhance decision-making, reduce biases in recruitment, and optimize workforce management (Bankins, 2021; Dahniar et al., 2024). For instance, AI-driven recruitment systems can streamline candidate selection by efficiently filtering applicants and predicting job-fit, addressing time and resource constraints (Wang et al., 2021).

Another critical factor, effort expectancy, refers to the perceived ease of use of AI technologies (Venkatesh et al., 2003). The adoption of AI is highly influenced by whether individuals find the technology intuitive and user-friendly. In Malaysia, the lack of technical expertise among workers underscores the importance of developing user-friendly AI systems and providing adequate training to facilitate adoption (Budhwar et al., 2023). Social influence, which refers to the extent to which individuals perceive that their peers or superiors expect them to use AI, is another significant predictor of behavioral intention (Venkatesh et al., 2003; Venkatesh, Thong, et al., 2012). Organizational culture, leadership support, and peer advocacy are essential in shaping employees' willingness to adopt new technologies (Chowdhury et al., 2023). In Malaysia, where workplace dynamics often emphasize collective orientation, social influence can have a particularly strong impact on AI adoption.

The availability of facilitating conditions such as infrastructure, technical support, and organizational readiness is also critical for the successful integration of AI (Venkatesh, Chan, et al., 2012). These conditions ensure that employees have the necessary resources to effectively use AI technologies in their daily tasks (Rajan & Baral, 2015). Behavioral intention serves as a mediator, linking these factors to the actual use of AI technologies. Without a strong intention to adopt AI, even the most advanced systems may remain underutilized (Venkatesh, Chan, et al., 2012).

This study contributes to the growing literature on AI adoption by focusing specifically on Malaysia's private sector workforce. By examining the relationship between performance expectancy, effort expectancy, social influence, and facilitating conditions, this research aims to provide actionable insights for policymakers and industry leaders. These insights will be crucial for encouraging AI adoption, ultimately improving organizational performance and competitiveness in a rapidly evolving digital landscape. The study also seeks to assess both the direct and indirect relationships between these factors and the actual use of AI, with behavioral intention serving as a mediating variable.

Literature Review

Underpinning Theory

The underpinning theory for this study is the Unified Theory of Acceptance and Use of Technology (UTAUT), developed by Venkatesh et al. (2003). UTAUT suggests that four core constructs, performance expectancy, effort expectancy, social influence, and facilitating conditions play a crucial role in determining individuals' behavioral intention to adopt and use technology, with behavioral intention subsequently influencing actual usage (Venkatesh et al., 2003; Venkatesh, Thong, et al., 2012). In the context of this study, performance expectancy refers to the degree to which individuals believe that adopting AI technologies will enhance their work efficiency and outcomes, such as improved decision-making, unbiased processes, and time savings (Budhwar et al., 2023; Dahniar et al., 2024). Effort expectancy relates to the perceived ease of learning and using AI technologies, emphasizing the need for intuitive systems and adequate training to support users, especially in contexts like Malaysia, where technology adoption levels may vary (Chatterjee & Bhattacharjee, 2020). Social influence examines the extent to which key stakeholders, such as organizational leaders or peers, encourage and normalize the adoption of AI, a factor particularly impactful in the collectivist and hierarchical cultural setting of Malaysia (Chowdhury et al., 2023; Venkatesh, Chan, et al., 2012). Facilitating conditions encompass the availability of resources, infrastructure, and organizational readiness that support the integration and implementation of AI systems (Rajan & Baral, 2015). Behavioral intention acts as a mediator, linking these constructs to the actual use of AI technologies. This framework provides a comprehensive model for analyzing the factors that influence AI adoption within the Malaysian private sector workforce.

Relationship between Performance Expectancy and Behavioral Intention

Performance expectancy, or the belief that adopting a technology will improve job performance, is a critical factor influencing behavioral intention (Venkatesh et al., 2003). In Malaysia's private sector, employees are increasingly recognizing the value of technologies like AI in boosting workplace efficiency, enhancing decision-making, and achieving competitive advantages. Research by Chatterjee and Bhattacharjee (2020) found that employees in private-sector organizations in Malaysia are more likely to adopt AI when they perceive it as a tool that can significantly improve their performance and productivity. Alam et al. (2019) also emphasize that the Malaysian workforce, particularly in sectors like finance, IT, and retail, views AI adoption favorably if it leads to better job outcomes, thereby increasing their intention to adopt the technology.

Relationship between Effort Expectancy and Behavioral Intention

Effort expectancy, which refers to the perceived ease of using a technology, is a major determinant of behavioral intention to adopt AI (Venkatesh et al., 2003). In the context of Malaysia's private sector, employees are more likely to embrace AI if the technology is perceived as user-friendly and easy to integrate into their daily work routines. If AI is seen as complex or requiring significant effort to learn, employees may be hesitant to adopt it. Alam et al. (2020) found that organizations that prioritize simple, intuitive AI interfaces and offer comprehensive training are more successful in encouraging employees across Malaysia's private sector to adopt AI. Rajan and Baral (2015) further highlight that reducing complexity and providing continuous support can significantly enhance employees' perceptions of AI's ease of use, especially in sectors with a high rate of technological adoption.

Relationship between Social Influence and Behavioral Intention

Social influence, or the perceived pressure from others to adopt technology, plays an important role in shaping behavioral intentions (Venkatesh et al., 2003). In Malaysia's private sector, social influence is particularly potent due to strong hierarchical structures and collective workplace cultures. Employees are often influenced by leadership's stance on AI adoption, as well as the attitudes and behaviors of their peers. Chowdhury et al. (2023) suggest that top management's endorsement and support for AI can positively affect employees' intention to adopt these technologies. In Malaysia's private sector, where corporate culture often prioritizes innovation, leadership's proactive approach to adopting AI can be a key motivator for employees to embrace AI (Budhwar et al., 2023). Social influence from peers also encourages adoption, as employees tend to follow the behaviors of colleagues who have already integrated AI into their work (Wang et al., 2021).

Relationship between Facilitating Conditions and Behavioral Intention

Facilitating conditions, such as the availability of resources, infrastructure, and organizational support, directly impact both behavioral intention and actual usage (Venkatesh et al., 2012). For employees in Malaysia's private sector, organizations that provide robust IT infrastructure, training programs, and technical support are more likely to see higher AI adoption rates. Menant et al. (2021) note that companies in Malaysia's private sector that proactively invest in upgrading their technological infrastructure and creating a supportive environment for learning AI significantly increase their employees' intention to adopt these technologies. Alam et al. (2020) further argue that access to training and support in AI helps overcome initial resistance and boosts employee confidence in adopting new technology. As Budhwar et al., (2023) ; Chowdhury et al. (2023) highlight, when employees have access to the necessary tools and support, their intention to use AI is enhanced.

Behavioral Intention as a Mediator Between Independent Variables and Actual Use

Behavioral intention is an important mediator between independent variables (performance expectancy, effort expectancy, social influence, and facilitating conditions) and actual use (Venkatesh et al., 2003). In Malaysia's private sector, employees who perceive AI as beneficial and easy to use are more likely to intend to adopt it. Chowdhury et al. (2023) found that in Malaysia, facilitating conditions such as training programs and leadership support directly influence employees' behavioral intention to adopt AI, which in turn influences their actual use. The relationship between these variables is crucial, as employees who form strong intentions based on positive perceptions of AI are more likely to successfully integrate the technology into their work.

Relationship between Behavioral Intention and Actual Use

Behavioral intention is a strong predictor of actual use, as employees who are motivated to adopt AI are more likely to use it in their day-to-day work (Venkatesh et al., 2012). Rajan and Baral (2015) found that employees in Malaysia's private sector, especially those in fast-paced, technology-driven industries like finance and retail, tend to follow through on their behavioral intention to adopt AI when the technology is perceived as beneficial to their work. Kelly (2024) highlight that when employees in the private sector are provided with sufficient training, support, and encouragement, their intention to adopt AI becomes actionable, leading to its actual use in the workplace. This underscores the importance of fostering strong behavioral intentions to ensure the successful implementation of AI technologies across the Malaysian private sector.

This literature review highlights the relationships among the independent variables (performance expectancy, effort expectancy, social influence, and facilitating conditions), the mediating variable (behavioral intention), and the dependent variable (actual use). The findings highlight the critical role of behavioral intention as a mediator, emphasizing that positive perceptions of technology, social support, and organizational resources collectively influence AI adoption in HRM.

Hence, the following hypotheses and research framework (*see Figure 1*) were proposed for this study:
H1: Performance expectancy has a positive relationship with behavioral intention to adopt AI among employees in Malaysia's private sector.
H2: Effort expectancy has a positive relationship with behavioral intention to adopt AI among employees in Malaysia's private sector.
H3: Social influence has a positive relationship with behavioral intention to adopt AI among employees in Malaysia's private sector.
H4: Facilitating conditions have a positive relationship with behavioral intention to adopt AI among employees in Malaysia's private sector.
H5: Behavioral intention mediates the relationship between performance expectancy and the actual use of AI among employees in Malaysia's private sector.
H6: Behavioral intention mediates the relationship between effort expectancy and the actual use of AI among employees in Malaysia's private sector.
H7: Behavioral intention mediates the relationship between social influence and the actual use of AI among employees in Malaysia's private sector.
H8: Behavioral intention mediates the relationship between facilitating conditions and the actual use of AI among employees in Malaysia's private sector.

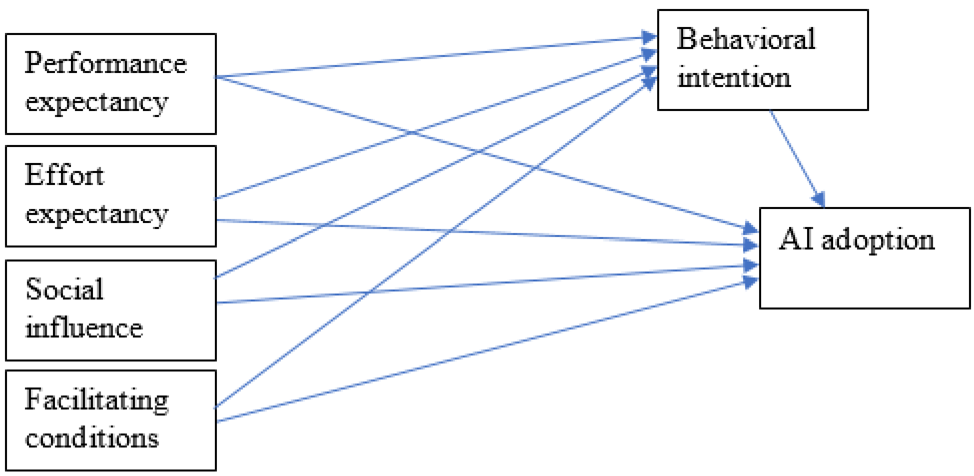

Figure 1: Research Framework

Methodology

This study adopts a quantitative research approach to explore the factors influencing the intention to adopt and use artificial intelligence (AI) among private sector employees in

Malaysia. The survey is designed based on the measurement tools for the independent variables (performance expectancy, effort expectancy, social influence, facilitating conditions), the mediating variable (behavioral intention), and the dependent variable (actual use). The items for each construct are adapted from established models, such as Venkatesh et al. (2003) and Rajan & Baral (2015). The respondents rated their perceptions on a Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). A convenience sampling technique was used and the final 276 clean responses, which is considered adequate for statistical analysis (Hair et al., 2017). Data was analyzed using SPSS to perform descriptive statistics, reliability testing, and correlation analysis. Structural Equation Modeling (SEM) was employed using SmartPLS version 4.0 to test the hypothesized relationships between the variables, assessing both direct and indirect effects. This analytical approach is to determine how performance expectancy, effort expectancy, social influence, and facilitating conditions influence behavioral intention, and how behavioral intention, in turn, affects actual use of AI among private sector's employees.

Data Analysis

Respondents Profile

Table 1 summarises the demographic characteristics of the respondents. The sample comprised a higher proportion of females (58.3%) than males (41.7%). In terms of age distribution, most respondents were between 26 and 35 years old (44.9%), followed by those aged 36–45 years (22.5%), indicating that the sample was dominated by young to mid-career professionals. Only a small fraction (5.8%) were aged 56 years and above. Marital status was relatively balanced, with 50.0% married and 48.6% single, while a negligible 1.4% were divorced. The majority of respondents possessed tertiary education, with 41.3% holding a bachelor's degree, 27.5% a diploma, and 14.1% a master's degree, reflecting a generally well-educated cohort. In terms of working experience, 41.7% reported more than ten years in employment, followed by 26.1% with two to five years, and 15.9% with less than one year. This suggests substantial representation from experienced professionals. The respondents were distributed across various industries, notably education (22.5%), services (22.1%), and healthcare (14.9%), with smaller proportions in manufacturing (12.3%) and IT/technology (9.1%). Overall, the demographic distribution reflects a diverse and well-qualified sample, suitable for examining perceptions and behavioural tendencies in a professional context.

Table 1
Descriptive Analysis of The Respondents (N=276)

Profiles	Frequency	Percentage (%)
Gender		
Male	115	41.7
Female	161	58.3
Age		
18 to 25 years	47	17.0
26 – 35 years	124	44.9
36 – 45 years	62	22.5
46 – 55 years	27	9.8
56 and above	16	5.8
Marital Status		
Single	134	48.6
Married	138	50.0

Divorce	4	1.4
Education Level		
SPM	37	13.4
Diploma	76	27.5
Bachelor's degree	114	41.3
Master's degree	39	14.1
PhD	3	1.1
Others	7	2.5
Years Of Working		
Less than 1 Year	44	15.9
2 – 5 years	72	26.1
6 – 10 years	45	16.3
More than 10 years	115	41.7
Industry		
Education	62	22.5
Manufacturing	34	12.3
Services	61	22.1
Healthcare	41	14.9
IT/Technology	25	9.1
Other	53	19.2

Measurement Model

Confirmatory Factor Analysis (CFA)

Confirmatory factor analysis (CFA) was employed to measure the relationship between latent variables and indicators assigned through the indicator loads (Ramayah et al., 2018). To confirm the CFA for the measurement model (outer model), this study employed matrices Hair et al. (2017) recommended, including convergent validity (loading and average variance extracted (AVE), discriminant validity and composite reliability (CR) for reflective indicators since this study employed reflective constructs. Table 2 indicates that all item factor loadings were more than 0.6, hence no items were deleted. Additionally, AVE values for all items were more than 0.5, and all CRs were more than 0.7. The convergent validity of the construct is satisfactory when AVE is above 0.5 and CR is greater than 0.7 (Ramayah et al., 2018).

Table 2

Summaries of Confirmatory Factor Analysis

Constructs	Item label	Loading	CR	AVE
		> 0.6	> 0.7	> 0.5
Actual Use (AU)	AU1: I use AI systems frequently in my work	0.912	0.917	0.843
	AU2: I depend on AI for completing job-related tasks	0.909		
	AU3: AI systems are an integral part of my work activities	0.933		
Behavioural Intention (BI)	BI1: I intend to use AI in my work regularly	0.884	0.942	0.853
	BI2: I predict that I will use AI in my work in the future	0.881		
	BI3: I plan to continue using AI for job-related tasks	0.965		
	BI4: I would recommend using AI to my colleagues	0.961		

Performance Expectancy (PE)	PE1: I find AI systems useful in my job	0.875	0.931	0.825
	PE2: Using AI enables me to accomplish tasks more quickly	0.913		
	PE3: AI improves my job performance	0.930		
	PE4: AI increases my productivity	0.915		
Effort expectancy (EE)	EE1: Learning how to use AI is easy for me	0.877	0.930	0.808
	EE2: My interaction with AI is clear and understandable	0.915		
	EE3: It is easy for me to become skillful at using AI	0.902		
	EE4: I find AI systems easy to use	0.901		
Social Influence (SI)	SC1: People who are important to me think I should use AI at work	0.856	0.907	0.778
	SC2: My colleagues who influence my behavior think I should use AI	0.883		
	SC3: My organization supports the use of AI systems	0.891		
	SC4: My supervisor encourages me to use AI	0.898		
Facilitating Conditions (FC)	FC1: I have the resources necessary to use AI	0.916	0.902	0.712
	FC2: I have the knowledge necessary to use AI	0.916		
	FC3: The AI system is compatible with other technologies I use	0.870		
	FC4: A specific person or group is available to assist me with AI difficulties	0.643		

Outer loading < 0.6, CR < 0.7, AVE < 0.5; item deleted due to low factor loading.

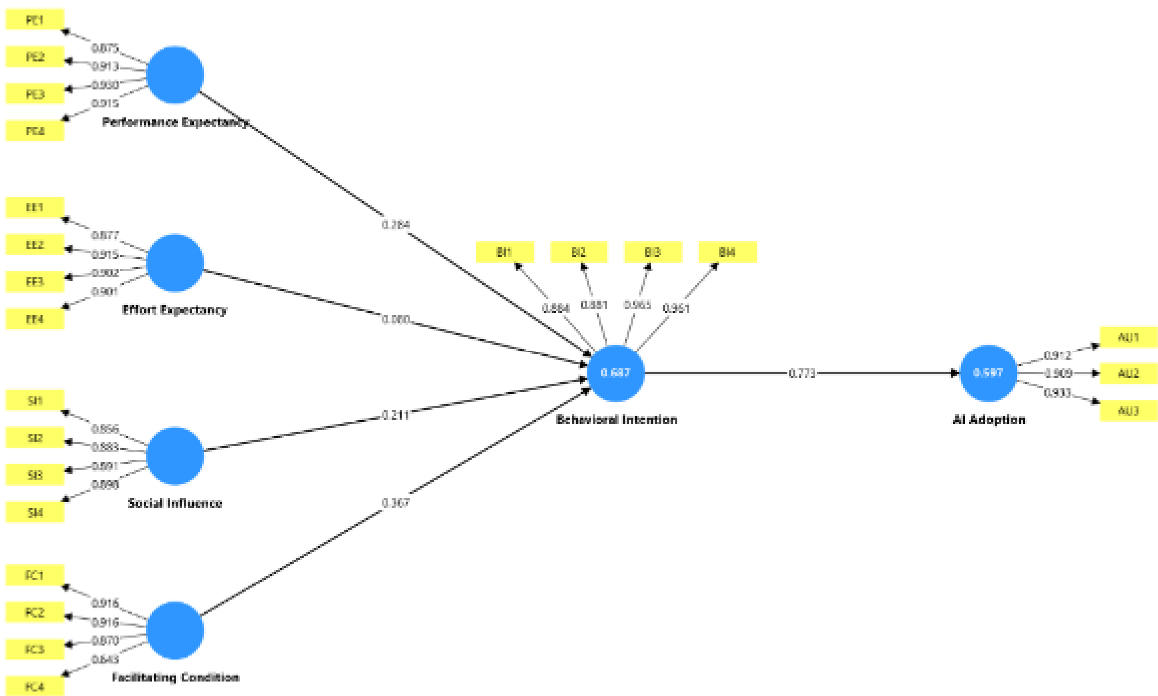

Figure 1: Measurement Model Path Diagram

Discriminant Validity

Subsequently, the discriminant validity of the model is assessed. This study employed all three methods in assessing the discriminant validity. Fornell and Lacker's criterion indicates all constructs load more strongly on their constructs than other constructs in the model. Besides, the shared variance between each construct and its indicators is greater than among other constructs (Ramayah et al., 2018). Also, using cross-loading, all indicators load high on its own construct but low on the other construct. This indicates that the constructs are distinctly different from each other. The third method of assessing discriminant validity is by using heterotrait-monotrait (HTMT). This study employed the cut-off value of 0.85 suggested by Kline (2011). As shown in Table 3, all the values fulfil the criterion of $HTMT_{090}$. This indicates that discriminant validity has been ascertained. To conclude, the discriminant validity at the construct level was established.

Table 3
HTMT Criterion

	AU	BI	EE	FC	PE	SI
Actual usage (AU)						
Behavioural Intention (BI)	0.828					
Effort Expectancy (EE)	0.757	0.759				
Facilitating Condition (FC)	0.865	0.828	0.860			
Performance Expectancy (PE)	0.628	0.759	0.801	0.705		
Social Influence (SI)	0.755	0.752	0.689	0.817	0.664	

Structural Model

Table 4 presents the results of the structural model assessment. The proposed model demonstrates robust explanatory power and predictive relevance. The coefficient of determination ($R^2 = 0.687$) indicates that 68.7% of the variance in Behavioural Intention (BI) is explained by Performance Expectancy (PE), Social Influence (SI), and Facilitating Conditions (FC), reflecting substantial explanatory capability. Furthermore, the cross-validated redundancy value ($Q^2 = 0.669$) confirms the model's predictive relevance, while the Variance Inflation Factor (VIF) values ranging from 2.191 to 3.493 remain below the threshold of 5, indicating no multicollinearity issues among predictors. Among the hypothesised relationships, three paths (H1, H3, and H4) were statistically significant, whereas one (H2) was not supported. Performance Expectancy ($\beta = 0.284$, $t = 3.775$, $p < 0.001$) significantly influenced Behavioural Intention, suggesting that perceived performance improvement drives adoption intention. Social Influence ($\beta = 0.211$, $t = 3.493$, $p < 0.001$) also exhibited a significant effect, implying that social endorsement and peer influence are key motivators for technology acceptance. Similarly, Facilitating Conditions ($\beta = 0.367$, $t = 4.976$, $p = 0.002$) positively affected Behavioural Intention, highlighting the importance of resource availability and institutional support in adoption decisions. In contrast, Effort Expectancy ($\beta = 0.080$, $t = 0.955$, $p = 0.340$) was not significant, indicating that ease of use does not meaningfully influence intention, possibly due to users' prior familiarity with similar technologies. Effect size (f^2) analysis further corroborates these findings. Facilitating Conditions exerted the largest effect on Behavioural Intention ($f^2 = 0.132$), followed by Performance Expectancy ($f^2 = 0.107$) and Social Influence ($f^2 = 0.065$), all of which indicate moderate effects (Cohen, 1988). Effort Expectancy ($f^2 = 0.006$) demonstrated a negligible effect. Overall, the results suggest that behavioural intention is predominantly shaped by perceptions of usefulness, social influence, and facilitating resources rather than ease of use.

Table 4
Hypothesis Testing of Direct Effect

Hypothesis	Path	β	SE	t-value	p-value	Decision	VIF	R^2	f^2	Q^2
H1	PE→BI	0.284	0.075	3.775	0.000***	Accepted	2.425	0.687	0.107	0.669
H2	EE→BI	0.080	0.084	0.955	0.340	Rejected	3.493		0.006	
H3	SI→BI	0.211	0.060	3.493	0.000***	Accepted	2.191		0.065	
H4	FC→BI	0.367	0.074	4.976	0.002***	Accepted	3.257		0.132	

**** Significant at 5% p<0.05 (one-tailed)*

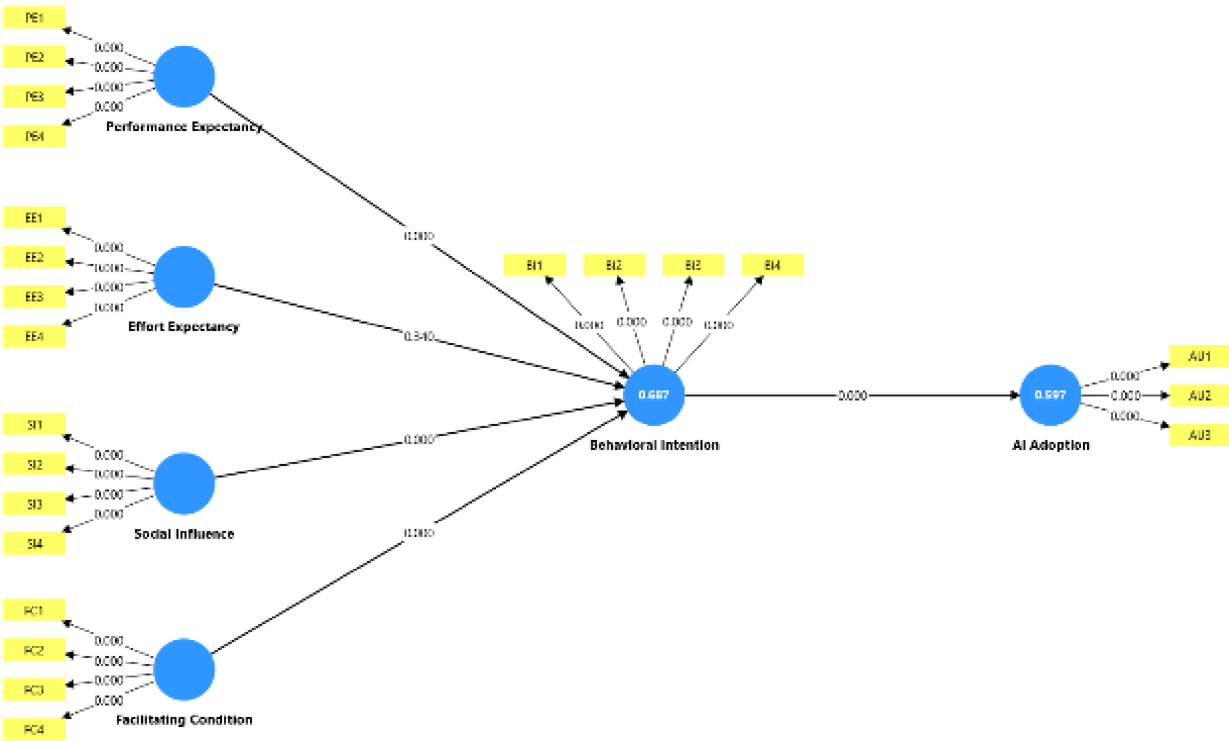

Figure 2: Structural Model Path Diagram

Mediating Results

Table 5 presents the results of the mediation analysis examining the indirect effects of Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC) on Actual Use (AU) through Behavioural Intention (BI). The findings reveal that BI significantly mediates the relationships between PE, SI, and FC with AU, while the indirect effect of EE on AU was not supported. Hence H5, H7 and H8 were accepted while H6 was rejected. Specifically, PE exerted a significant indirect effect on AU via BI ($\beta = 0.220$, $t = 3.910$, $p < 0.001$), indicating that individuals who perceive technology as enhancing performance are more likely to translate this perception into actual use through stronger behavioural intention. Similarly, SI demonstrated a significant mediating effect ($\beta = 0.163$, $t = 3.443$, $p < 0.001$), suggesting that social endorsement and normative influence enhance users' intention, which in turn drives technology utilisation. FC also showed a significant indirect influence ($\beta = 0.283$, $t = 4.874$, $p = 0.001$), highlighting that adequate infrastructural and organisational support facilitate behavioural intention that leads to actual adoption behaviour. Conversely, the indirect effect of EE on AU ($\beta = 0.062$, $t = 0.941$, $p = 0.347$) was not statistically significant, implying that ease of use does not meaningfully strengthen the intention–behaviour link in this context. Collectively, these findings confirm the mediating role of behavioural intention in translating perceptions of usefulness, social influence, and enabling conditions into actual technology use, consistent with the Unified Theory of Acceptance and Use of Technology (UTAUT).

Table 5
Hypothesis Testing of Indirect Effect

Hypothesis	Path	β	SE	t-value	p-value	LL	UL	Decision
H5	PE→BI→AU	0.220	0.056	3.910	0.000***	-0.068	0.190	Accepted
H6	EE→BI→AU	0.062	0.066	0.941	0.347	0.167	0.396	Rejected
H7	SI→BI→AU	0.163	0.047	3.443	0.000***	0.115	0.330	Accepted
H8	FC→BI→AU	0.283	0.058	4.874	0.001***	0.079	0.262	Accepted

**** Significant at 5% p<0.05 (one-tailed)*

Discussion

The findings provide empirical support for the Unified Theory of Acceptance and Use of Technology (UTAUT) in explaining AI adoption among Malaysia's private sector workforce. Performance Expectancy, Social Influence, and Facilitating Conditions were found to significantly influence employees' intention to use AI, while Effort Expectancy was not significant. Employees are more likely to adopt AI when they believe it enhances job efficiency and productivity, and when support from supervisors, peers, and organizations is evident. This emphasizes the importance of leadership advocacy, a supportive culture, and resource availability in promoting AI integration at the workplace.

The mediation analysis further confirms that Behavioural Intention acts as a key link between perceptions and actual AI usage. Employees who view AI as useful, socially supported, and backed by sufficient infrastructure are more likely to engage in consistent use. Overall, organizational support, performance benefits, and social endorsement emerge as the main enablers of AI adoption, suggesting that private sector organizations should focus on strengthening technical support systems and fostering positive attitudes toward AI for sustained implementation.

Theoretical Implications

This study extends the UTAUT framework by incorporating behavioral intention as a mediator in the relationship between performance expectancy, effort expectancy, social influence, facilitating conditions, and actual use of AI in Malaysia's private sector. It advances theoretical understanding by providing insights into the socio-cultural and organizational factors that influence AI adoption in an emerging market context, emphasizing the need for context-specific models. The findings emphasize the critical role of facilitating conditions in bridging the gap between employees' behavioral intention and actual use of AI, offering a nuanced perspective on the framework. The study reinforces the mediating role of behavioral intention in linking key determinants to actual AI use, contributing to the refinement and practical applicability of technology adoption theories.

Contextual Implications

This research highlights specific factors influencing AI adoption within Malaysia's private sector workforce, offering empirical insights into the challenges and opportunities unique to the country's economic and cultural environment. It highlights the importance of addressing workforce readiness through targeted training and awareness initiatives, tailored to the private sector's needs in Malaysia. The findings provide industry-specific recommendations by identifying sectors within Malaysia's private sector that are either more resistant to or prepared for AI adoption, guiding focused interventions.

Practical Implications

Organizations in Malaysia's private sector should implement tailored training programs that enhance employees' effort expectancy and simplify the use of AI technologies to improve confidence and efficiency. Companies need to strengthen facilitating conditions by ensuring adequate resources, technical support, and system compatibility to bridge the gap between intention and actual AI use. Leadership should leverage social influence by fostering a culture of collaboration and peer support to positively influence employees' behavioral intentions toward adopting AI. Reward systems should be designed to incentivize employees' behavioral intention to use AI by linking their efforts to tangible benefits and usage metrics, creating a culture of motivation and engagement. Policymakers should create comprehensive guidelines that support AI integration in Malaysia's private sector by addressing workforce readiness, providing technical resources, and ensuring equitable access to technology. Organizations can use the insights from this study to align their workforce development strategies with Malaysia's broader goals of innovation, sustainability, and economic growth, ensuring a resilient and future-ready workforce.

Suggestions for Future Study

Future studies could explore the impact of individual differences, such as age, education, and digital literacy, on AI adoption in Malaysia's private sector, examine the role of organizational culture and leadership styles in fostering a supportive environment for AI integration, and investigate how industry-specific factors or regional differences within Malaysia influence employees' perceptions and actual use of AI, while also expanding the scope to public sector in Malaysia or similar emerging markets to provide more comprehensive insights into the factors that drive or hinder AI adoption.

Conclusion

This study examined the key factors influencing AI adoption among employees in Malaysia's private sector, based on the Unified Theory of Acceptance and Use of Technology (UTAUT). The findings confirm that performance expectancy, social influence, and facilitating conditions significantly shape behavioural intention, which in turn drives actual AI usage. Effort expectancy, however, was not a significant predictor. The results highlight that successful AI adoption depends on employees' perceptions of usefulness, organisational support, and leadership encouragement. Strengthening training initiatives, technical infrastructure, and peer support systems can enhance workforce readiness and bridge the gap between intention and actual use. The study contributes to the extension of UTAUT in an emerging economy context and provides practical insights for organisations and policymakers aiming to foster a digitally capable and AI-ready workforce.

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