The 2nd ASEAN School of Business Network International Conference 2025

www.aseansbn.org August 7-8, 2025 Negeri Sembilan, Malaysia

Building a Future-Ready Public Sector with AI: Enabling an Actionable AI Framework

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ABSTRACT

As ASEAN economies pursue inclusive and sustainable growth, Artificial Intelligence (AI) has emerged as a significant disruptive force in public sector transformation, reshaping decision-making and strategic planning. Despite its potential to streamline processes and enhance service delivery, AI adoption within the Malaysian public sector remains under-optimised. While the 2024 Government AI Readiness Index ranks Malaysia second in ASEAN and 23rd globally, the country has declined in the Chandler Good Government Index particularly in the innovation indicator, where it falls below the global average. In light of these trends, it is vital for the Malaysian government to understand the key factors influencing AI adoption among public sector managers, who act as pivotal change agents in implementing AI-related policies and navigating adoption challenges. This study addresses that need by employing the Unified Theory of Acceptance and Use of Technology (UTAUT), extended with AI literacy as a moderating variable. Drawing on survey data from 402 public sector managers in Putrajaya, Kuala Lumpur, and Selangor, the findings show that Performance Expectancy is the strongest predictor of AI adoption, followed by Effort Expectancy and Facilitating Conditions. Although Social Influence is statistically significant, its impact is weaker, reflecting the hierarchical and compliance-driven nature of Malaysia's public sector. Notably, AI literacy moderates this relationship, with digitally literate managers exhibiting greater autonomy and confidence in AI-related decision-making. In response to these findings, the study proposes an actionable AI framework to support strategic and sustainable adoption. The framework offers a practical model for strengthening institutional capabilities, fostering data-driven governance, and building a future-ready public sector aligned with ASEAN's digital transformation agenda.

Keywords: AI Adoption, Public Sector, UTAUT

DOI: https://doi.org/10.64458/asbnic.v2.57

INTRODUCTION

The term AI, first introduced by John McCarthy in 1956, refers to machines that can emulate human intelligence (Burgos, 2024; McCorduck, 2004). The functions of AI that include perception, reasoning, learning, interacting, solving problems, making decisions and demonstrating creativity (Brendel, 2021; Krafft et al., 2021) extends beyond traditional machine capabilities typically associated with machine operations handled by skilled machinists, where it performs cognitive tasks similar to human intelligence (Aphirakmethawong, Yang & Mehnen, 2022). AI has the capacity to operate as an intelligent system, utilising data, analysis, and observations to autonomously carry out specific tasks without being explicitly programmed for those tasks (Burgos, 2024; Reim et al., 2020).

The advancement of AI has sparked significant academic interest, with studies delving into the real-world impacts and consequences of AI. The ability of AI to emulate human capability is paving the way for new possibilities (Burgos, 2024), where AI emerges as a transformative force in various sectors such as healthcare, medical imaging and diagnostics (Dai & Singh, 2021; Jain et al., 2022; Vaishya et al., 2020; Zhang et al., 2021), manufacturing (Zhou & Wang., 2021), banking and digital payments (Khando et al., 2022), education (Fryer et al., 2020; Vincent-Lancrin & Vlies, 2020), supply chain management (Pournader et al., 2021), cyber security (Sagar et al., 2020; Sedjelmaci, 2021) and transportation and autonomous vehicle (Ma et al., 2020).

Consequently, governmental organisations have shown a growing interest in utilising AI to improve public service delivery and administrative processes (van Noordt & Misuraca, 2020; Burgos, 2024). The adoption of AI in the public sector also holds significant potential to streamline operations, enhance decision-making and improve public service delivery (Ho et al., 2022; Samsurijan et al., 2022). The use of generative AI, a category of AI technology that can generate new content, ranging from text, images and music to code and synthetic data, for example, offers significant use for organisations to accelerate work tasks (Kaldero, 2024).

In many parts of ASEAN, the deployment of AI remains in its developmental stage, with many nations have yet to harness its full potential (Agustono et al., 2023). While efforts have been made especially in strengthening data infrastructure and establishing governance frameworks, the overall preparedness for AI adoption varies widely among member states. This disparity is reflected in the 2024 Government AI Readiness scores, where, among the 10 ASEAN Member States, Singapore continues to lead with a high overall score of 84.3, maintaining its top position since 2020. In contrast, countries like Philippines (58.5), Brunei Darussalam (55.5), Lao PDR (36.1), Cambodia (36.6) and Myanmar (34.3), rank at the lower end of the spectrum. These scores highlight substantial gaps in digital infrastructure, institutional capacity and strategic implementation, all of which hinder their ability to develop and integrate AI technologies effectively (Oxford Insights, 2024).

For Malaysia, the country ranks second among ASEAN Member States in the 2024 Government AI Readiness Report with an overall score of 71.4 (Oxford Insights, 2024), reflecting notable progress in key areas of AI development. Its strong performance is supported by improvements across three core pillars - 82.5 in the Government pillar, indicating robust leadership and policy frameworks, 77.6 in Data & Infrastructure, reflecting a growing digital foundation, and 54.2 in the Technology Sector, suggesting moderate maturity within its innovation ecosystem (Oxford Insights, 2024). However, despite these advancements, Malaysia experienced a decline in its standing on the Chandler Good Government Index (2024;2025), dropping from rank 39th globally in 2024 to 44th in 2025. The country continues to fall below the global average on the innovation indicator, pointing to persistent challenges in fostering innovation. Although the country made an 11-spot jump in the IMD World Competitiveness Ranking from 34th position in 2024 to 23rd in 2025 (IMD, 2025), it lags innovation capabilities and digital transformation especially in adopting new technologies and nurturing new generation of future-ready workers (Abdul Aziz, 2025).

Prior studies have acknowledged that distinctive regional challenges such as restrictive legal frameworks, cultural diversity and uneven progress in digital infrastructure continue to hinder the widespread adoption of AI across ASEAN nations (Cheng & Hackett, 2020; Budhwar et al., 2023). However, the scope and impact of these barriers vary significantly across countries, shaped by differences in cultural norms, institutional capacities, and regulatory environments (Xiang et al., 2023). As such, effectively addressing these disparities requires tailored, country-specific strategies that align AI integration with each nation's socio-political context and infrastructural readiness. These persistent barriers underscore the importance of localized policy frameworks and investment approaches to enable inclusive and sustainable AI deployment across the region.

Therefore, this study aims to investigate the determinants of AI adoption in the Malaysian public sector using the Unified Theory of Acceptance and Use of Technology (UTAUT) model. Studies by Ismail (2024), Menon and Shilpa (2023), Wang et al. (2024), Xu (2024) and Young et al. (2024) have highlighted the relevance of UTAUT in AI adoption studies across countries such as China, South Korea and India, which rank in the top 20 of the Global AI Index (Tortoise, 2023). Nevertheless, the literature specific to the Malaysian context is limited and predominantly focuses on the educational sector (Mohd Rahim et al., 2022; Mohsin et al., 2024; Sayed Abul Khair et al., 2023; Zainol, 2023). As such, utilising the UTAUT model from the Malaysian public sector perspective could aid policymakers in overcoming barriers to AI adoption, enhancing user acceptance and maximising the benefits of AI across various sectors.

LITERATURE REVIEW

Overview of Artificial Intelligence

The history of Artificial Intelligence (AI) reflects a dynamic progression of scientific innovation, technological development and societal impact. Early AI efforts began in the 1950s with pioneers such as Allen Newell and Herbert Simon, followed by foundational contributions from Marvin Minsky and John McCarthy (Gómez-Caicedo et al., 2022; Park & Park, 2018). Since then, AI has undergone cycles of rapid progress and stagnation, referred to as AI winters, eventually giving rise to today's advanced technology like deep learning and neural networks (Wang & Wang, 2017; Pasquinelli & Joler, 2020). AI's evolution highlights its increasing relevance in both scientific and societal domains. It encompasses a broad range of intelligent systems capable of performing tasks such as learning, problem-solving, language processing, and decision-making (Joiner, 2018; Reinhardt, 2023; Von Krogh, 2018). These systems rely on algorithms to process various types of input such as text, audio, images, and numbers to generate actionable outputs. Wyman (2018) classifies AI functions into five categories namely classification, prediction, clustering, creation, and learning. Similarly, Davenport (2019) outlines eight broad cognitive capabilities, ranging from automating tasks and data processing to understanding language, recognizing images and navigating autonomously. These functions have been translated into key technologies such as Machine Learning (ML), Natural Language Processing (NLP) and Robotic Process Automation (RPA).

Significant progress in AI technologies has influenced the operations of governmental agencies, by way of redefining the regulatory role of government and transforming the interaction between governments and citizens (Eggers et al., 2017). When integrated into the public sector, AI's potential spans various sectors such as legal systems, construction, R&D, education, telecommunication, transportation, data security, management, policymaking, finance and healthcare (Assemi, Paz, & Baker, 2021). AI's role in providing government services also extends to optimizing utilisation, accurate forecasting, simulating complex systems and formulating policies for environmental monitoring and management, urban planning, motor vehicle navigation, and distribution logistics (Sharma, Yadav, & Chopra, 2020; Zuiderwijk, Chen, & Salem, 2021).

AI in the Malaysian Public Sector

In recent years, the adoption of AI in Malaysia's public sector has accelerated, driven by the national digital transformation agenda encapsulated in the Malaysia Digital Economy Blueprint (MyDIGITAL). This comprehensive policy framework outlines a strategic vision to transform Malaysia into a digitally driven, high-income nation and a regional leader in the digital economy (EPU, 2021). Central to this vision is the promotion of AI through targeted investments in talent development, cross-sector partnerships and public awareness initiatives (EPU, 2021). A key initiative under MyDIGITAL is AI Untuk Rakyat (AI for the Citizen), a free online self-learning platform designed to enhance AI literacy among the public (MOSTI, 2021; Mohamed Radhi, 2024). Notably, public sector employees are required to complete the programme, mandated by a circular issued by the Director-General of Public Services (Povera, 2024). This reflects a broader effort to ensure foundational AI knowledge across the civil service and to foster a digitally competent workforce.

The establishment of the National Artificial Intelligence (AI) Office under the National AI Roadmap 2021–2025 functions as a central coordinating entity responsible for aligning AI strategies with national priorities, facilitating policy development and managing implementation efforts across government, academia and industry stakeholders (MOSTI, 2021). Its core responsibilities include developing ethical AI governance frameworks, coordinating AI talent pipelines, and integrating AI technologies to enhance public service delivery and operational efficiency such as through predictive analytics and process automation. This effort aligns with the importance of centralized governance in the effective deployment of AI, as highlighted by Thian (2025) and Totonchi (2025), who argue that institutional mechanisms such as the AI Office are critical for overcoming fragmented policy implementation and ensuring alignment with national values and regulatory standards. These scholars also emphasize the role of such entities in fostering institutional readiness, reducing policy ambiguity and enhancing accountability across public institutions. However, the long-term success of centralized AI governance is contingent upon sustained political will, effective inter-agency collaboration and the ability to swiftly adapt to evolving technological and regulatory environments (Dhillon et al., 2024; Talib et al., 2025).

While Malaysia's public sector demonstrates both the intent and foundational structures necessary for AI adoption, it must still address persistent challenges such as organizational silos, workforce capability gaps and uneven digital infrastructure. The integration of AI into public service delivery introduces complex and unprecedented scenarios, underscoring the critical need for both practitioners and researchers to understand, evaluate and respond to these emerging dynamics (Dwivedi et al., 2021).

Critical Success Factors in AI Adoption

Numerous studies have identified key factors influencing successful AI adoption, including organisational readiness (Felemban, Sohail & Ruikar, 2024; Lee & Kim, 2021), knowledge and awareness (Park & Lee, 2019; Wang & Smith, 2020), trust and ethical considerations (Pechtor & Basl, 2023), integration with existing processes (Zhang & Lu, 2021), organisational agility (Smith & Johnson, 2021), and regulatory and policy challenges (Erdélyi & Goldsmith, 2020). These factors collectively shape AI adoption across various sectors and are elaborated below.

Knowledge and Awareness. A clear understanding of AI's capabilities and limitations is vital for adoption. Lack of awareness can hinder acceptance and funding mobilisation. Studies by Merhi (2023), Hamm and Klesel (2021) as well as Russell and Norvig (2016) highlight that informed organisations are better equipped to adopt AI effectively.

Trust and Ethical Considerations. Trust and ethical awareness, especially around data protection and privacy, are essential in public sector adoption (Pechtor & Basl, 2023; Murdoch, 2021). While strict regulations may restrict scalability, technical solutions like encryption (Acar et al., 2020) can enable secure adoption. This requires moving beyond traditional approaches toward new governance models.

Organisational Readiness. Readiness encompasses strategic alignment, leadership support, digital maturity and infrastructure (Jöhnk et al., 2020; Agarwal, 2022). Factors such as cost-effectiveness, vendor support and AI-specific governance structures also contribute to adoption (Pillai & Sivathanu, 2020; Kurup & Gupta, 2022; Radhakrishnan & Chattopadhyay, 2020).

Integration With Existing Processes. Successful AI adoption depends on smooth integration with existing workflows. Organisations must align AI with human-centric processes to avoid disruption and ensure operational efficiency (Chui, Manyika & Miremadi, 2017; Davenport, 2019).

Organisational Agility. Agility enables organisations to quickly adapt to technological shifts, seize AI opportunities and revise strategies as needed (Teece, 2018; Prieto, Revilla & Rodriguez-Prado, 2017).

Regulatory and Public Policy Challenges. Governments play a pivotal role in addressing ethical, legal and social implications of AI. Effective governance frameworks must ensure transparency, privacy and alignment with societal values (Floridi et al., 2018; Wachter, Mittelstadt & Floridi, 2017; Taddeo & Floridi, 2018).

Unified Theory of Acceptance and Use of Technology (UTAUT) Model

The Unified Theory of Acceptance and Use of Technology (UTAUT) is an extensive explanatory framework developed to clarify and predict the acceptance and utilisation of technology in various fields. Venkatesh, Morris, Davis, and Davis (2003), in the development of UTAUT, articulated the objectives of their study, which involved a comprehensive review, discussion and comparison of eight prominent models in the realm of technology acceptance namely the Theory of Reasoned Action (TRA) (Ajzen & Fishbein 1980); Technology Acceptance Model (TAM) (Davis, 1989); Motivational Model (MM) (Davis et al., 1992); Theory of Planned Behaviour (TPB) (Ajzen, 1991); Combined TAM and TPB (C-TAM-TPB) (Taylor & Todd, 1995); the model of PC utilisation (PCU) (Thompson et al., 1991); Innovation Diffusion Theory (IDT) (Rogers, 1995); and Social Cognitive Theory (SCT) (Bandura, 1986).

UTAUT's validity and reliability have been rigorously tested in numerous studies (Dowdy, 2020; Khan et al., 2021; Šumak & Šorgo, 2016; Venkatesh et al., 2003). UTAUT has been applied in diverse studies, including mobile payment applications (Hadi et al., 2022), green farmer adoption (Siregar et al., 2022), online banking (Riffai et al., 2012), e-government services (Mansoori et al., 2018) and library management (Zainab et al., 2018). UTAUT remains one of the most extensively studied and widely applied theories for understanding emerging technology acceptance, as evidenced by its application in various studies such as cryptocurrency (Kala & Chaubey, 2023), internet banking (Rahi & Abd. Ghani., 2019), blockchain (Tran & Nguyen, 2021) and e-government (de Freitas & da Rosa, 2022). These applications demonstrate the versatility of the UTAUT model in understanding technology adoption and use across different domains, and the model continues to be a valuable framework for understanding and predicting user acceptance and technology adoption (Behl et al., 2021; Chao, 2019; Fujimori et al., 2022; Gado et al., 2021).

UTAUT identifies four key determinants of technology adoption as its independent variable, namely performance expectancy, effort expectancy, social influence, and facilitating conditions, as well as one dependent variable, which is behavioural intention. Each of these variables is further explained in the sections below.

Behavioural Intention (BI). BI reflects an individual's likelihood of adopting a technology, shaped by perceptions of usefulness, ease of use, social norms and institutional support. Its predictive role in adoption has been affirmed in various studies (Bakheet & Gravell, 2019; Gohil, 2023). In this study, BI is measured by respondents' intention, prediction and plan to use AI in the future (Venkatesh et al., 2003).

Performance Expectancy (PE). PE refers to the belief that using technology enhances job performance. It remains a primary driver of adoption, especially in task-related contexts (Owusu Kwateng et al., 2019; Avci, 2022).

Effort Expectancy (EE). EE captures the perceived ease of using technology. Technologies that are user-friendly are more likely to be accepted (Handayanto & Ambarwati, 2022).

Social Influence (SI). SI denotes the perceived pressure from others to adopt a technology. In organisational settings, peer behaviour, leadership support and cultural norms significantly affect adoption decisions (Avci, 2022).

Facilitating Conditions (FC). FC relates to the perceived adequacy of organisational and technical infrastructure to support technology use. Strong support systems can enable smoother adoption (Handayanto & Ambarwati, 2022).

AI Literacy

AI literacy is becoming increasingly critical as AI technologies are progressively integrated into organisational operations. While artificial intelligence refers to the development of systems capable of making autonomous decisions, effectively simulating and extending human intelligence (Celik, 2023; McCarthy, 2007), AI literacy is defined as the ability to understand, evaluate and apply AI technologies effectively. It encompasses the knowledge, skills and competencies required to engage with AI systems, algorithms, and tools (Malik, 2023). The core components of AI literacy include active engagement with AI tools and a conscious understanding of related ethical issues (Celik, 2023; Steinbauer et al., 2021). Unlike traditional definitions of literacy, which focus on reading and writing, AI literacy includes the ability to comprehend AI functionality (Willinsky, 2017), its underlying techniques, limitations and societal implications (Celik, 2023; Kreinsen & Schulz, 2023).

One prominent instrument for measuring AI literacy is the AI Literacy Scale (AILS), developed by Wang, Rau, and Yuan (2023). This scale is grounded in digital literacy frameworks proposed by Balfe, Sharples and Wilson (2018) and Calvani et al. (2008). AILS comprises four dimensions namely awareness, usage, evaluation and ethics and is specifically designed to assess the level of AI literacy among non-experts (Celebi et al., 2023).

Awareness. This dimension assesses an individual's foundational understanding of artificial intelligence, including the ability to distinguish between AI-driven and non-AI technologies. It involves recognizing the presence of AI in everyday applications and appreciating its relevance and potential. Awareness serves as the entry point to AI literacy by shaping perceptions of AI's significance in various contexts.

Usage. This dimension focuses on an individual's technical ability to engage with and apply AI tools in practical settings, that includes proficiency in using AI-enabled systems such as data visualization software, automated workflows and conversational agents (e.g., chatbots). It also involves adaptability in learning new AI systems and overcoming initial usage challenges. This dimension evaluates not only the capacity to use AI but also the effectiveness in leveraging these tools for productivity, decision-making and problem-solving.

Evaluation. This dimension measures the individual's ability to critically assess the functionality, accuracy, and limitations of AI applications. It involves understanding the assumptions underpinning AI models, identifying potential biases, and interpreting AI outputs within appropriate contexts. Evaluation is essential for ensuring responsible and informed use of AI systems.

Ethics. This dimension addresses an individual's awareness and application of ethical considerations when interacting with AI. These include data privacy, algorithmic bias, information security, and the responsible handling of sensitive data. Ethical literacy ensures that users are attuned to the societal and legal implications of AI and helps align AI use with human rights and regulatory standards.

RESEARCH METHOD

Research Design

This study adopts a causal cross-sectional research design to examine cause-and-effect relationships between key variables associated with AI adoption and literacy. Using a field survey, the study employs a non-experimental quantitative approach, allowing data collection in a natural organisational setting without manipulating independent variables (Babbie, 2020). The research focuses on identifying the strength and direction of relationships among variables (Fraenkel, Wallen, & Hyun, 2011), which is valuable for understanding behavioural patterns within organsational contexts.

Unit of Analysis

The unit of analysis for this study comprises Malaysian public sector managers within the Management and Professional Group, specifically those holding Grades 41 to 54, the managerial ranks within Malaysia's public service, serving in government offices in Putrajaya, Kuala Lumpur, and Selangor. It is important to contextualize that the Malaysian public sector workforce is classified into three hierarchical groups by the Public Service Department (Mohd Adnan, Aminudin, & Jamaiudin, 2023), reflecting varying degrees of responsibility, decision-making authority and strategic involvement.

The first category is the Top Management Group, consisting of officers in Premier Grade C and above. This includes high-ranking positions such as Secretaries-General, Directors-General and other senior executives responsible for policy formulation, strategic direction and inter-agency coordination. They play a pivotal role in shaping national priorities, long-term development agendas and ensuring alignment with overarching government objectives.

The second category, and the focus of this study, is the Management and Professional Group (Grades 41 to 54). This group forms the core operational and technical leadership within the civil service, encompassing professionals such as Assistant Directors, Principal Officers and Heads of Divisions. These officers are primarily responsible for policy implementation, programme oversight and administrative management across ministries and agencies. They are divided into three managerial levels namely junior (Grades 41-44), middle (Grades 48–52) and senior (Grades 54–56) (INTAN, 2024). Positioned between top leadership and support staff, these managers serve as key drivers of public sector transformation, particularly in relation to digitalisation and AI adoption.

The third category is the Implementer or Support Group, comprising personnel from Grades 19 to 40. This group includes technical, clerical and frontline staff who provide critical administrative and operational support. While their influence on policymaking is limited, their role is essential to the effective delivery of public services and the practical application of AI technologies at the operational level.

The selection of the Management and Professional Group as the unit of analysis is particularly appropriate, as these officers are seen as managers who serve as intermediaries and translate strategic directives into actionable initiatives. As highlighted by Zainun, Johari and Adnan (2021), these officers are directly engaged in the planning, coordination, monitoring and execution of government programmes and projects. This positions them ideally to offer valuable insights into AI-related organisational dynamics. Moreover, their dual role of bridging top-down policy formulation with bottom-up implementation makes them critical stakeholders in understanding the behavioural and structural factors influencing AI adoption within the public sector. Additionally, the minimum entry qualification for the Management and Professional Group is a bachelor's degree, whereas the Implementer/Support Group typically requires a diploma or secondary school certificate (Malay Mail, 2024). This distinction reflects a higher level of academic preparation and analytical competency, reinforcing their suitability as respondents for exploring complex issues such as AI adoption and literacy.

Data Collection

Data was collected through a self-administered online questionnaire using Google Forms, a cost-effective and efficient method for reaching large samples (Dahabreh, 2023; Rea & Parker, 2014). This approach has been widely adopted in various disciplines including education, healthcare and social sciences (e.g., Hindrasti & Sabekti, 2020; Pillay et al., 2020). The method allows respondents to complete the survey at their convenience, encouraging more candid responses (Dillman, 2009), and supports generalisability and replication (Mikalef et al., 2022). Ethical approval was obtained from the University's Research Ethics Committee, ensuring adherence to institutional standards and protection of participants' rights (Yadav, 2023). A cover email was distributed, detailing the study purpose, voluntary participation, anonymity and confidentiality, accompanied by a confirmation letter from the University. A clear deadline was set to ensure timely responses. Sample size considerations followed established guidelines with 377 respondents recommended for a population of 20,000 (Sekaran, 2011) and over 200 for SEM analyses (Hair et al., 2017; Kline, 2016). Given the total population of 132,761 public sector managers in Putrajaya, Kuala Lumpur, and Selangor (Public Service Department Malaysia, personal communication, 24 October 2024), a target sample size of 400 was set.

RESULTS

A total of 402 public sector managers participated in the study. The majority were aged 41–50 (50.0%), followed by 31–40 (33.6%), 51 and above (10.9%), and 30 and below (5.5%). In terms of education, 48.5% held a Master's degree, 44.5% a Bachelor's, and 7.0% a PhD. Qualifications below a Bachelor's degree were excluded, as managerial roles require degree-level entry (JPA, 2024). Respondents represented 18 of 21 public service schemes, with the largest share from the Administration and Diplomatic scheme (37.8%), followed by Social (12.4%), Finance (10.4%), Information System (7.5%), Education (5.7%), and Engineering (5.5%). Other schemes contributed less than 5% each; no responses were received from Transport, Police, or Skills schemes due to sampling limitations. By management level, 46.0% were in junior management (Grades 41-44), 43.8% in middle (Grades 48–52) and 10.2% in senior roles (Grades 54–56). Years of service ranged from over 21 years (20.1%) to 5 years or less (13.2%), with 30.6% having 16–20 years and 25.6% with 11–15 years. All respondents (100%) had heard of AI. Notably, 68.9% had attended AI-related training, and 91.5% reported prior use of AI, reflecting a high baseline of AI awareness and engagement.

Table 1. Demographic Profile of Respondents

Demographics	Sample (N=402)	Proportion (%)
Age		
30 years old and below	22	5.5%
31 - 40 years old	135	33.6%
41 - 50 years old	201	50.0%
51 years old and above	44	10.9%
Highest Education Level		
Bachelor's Degree	179	44.5%
Master's Degree	195	48.5%
Doctor of Philosophy	28	7.0%
Service Classification		
Administration and Diplomatic	152	37.8%
Social	50	12.4%

Demographics	Sample (N=402)	Proportion (%)
Finance	42	10.4%
Information System	30	7.5%
Education	23	5.7%
Engineering	22	5.5%
Research and Development	15	3.7%
Medical and Health	15	3.7%
Security and Public Defense	12	3.0%
Science	10	2.5%
Administrative and Support	9	2.2%
Economy	8	2.0%
Talent and Art	4	1.0%
Law and Judiciary	4	1.0%
Agriculture	3	0.7%
Prevention	1	0.2%
Maritime Enforcement	1	0.2%
Malaysia Armed Forces	1	0.2%
Current Managerial Level		
Junior Management	185	46.0%
Middle Management	176	43.8%%
Senior Management	41	10.2
Years in Service		
5 years and below	53	13.2%
6 - 10 years	42	10.4%
11 - 15 years	103	25.6%
16 - 20 years	123	30.6%
21 years and above	81	20.1%
Heard of AI		
Yes	402	100%
No	0	0%
AI Training		
Yes	277	68.9%
No	125	31.1%
Use of AI		
Yes	368	91.5%
No	34	8.5%

Descriptive Statistics

Descriptive statistics were used to assess the dataset's distribution, focusing on mean, standard deviation, skewness, and kurtosis (Saunders et al., 2019). Independent variables (PE, EE, FC, SI) were measured using a 5-point Likert scale, while the dependent variable, Behavioural Intention (BI), was assessed using a 7-point scale to capture more refined intention levels. Mean scores indicated high agreement for PE, EE, FC, and BI. Social Influence (SI) showed moderate agreement overall, with item SI8 showing high agreement. Standard deviations for PE, EE and FC ranged from 0.6 to 0.9, reflecting response consistency. In contrast, SI items SI1, SI3 and SI5 had higher deviations (above 1.08), suggesting greater variability. For BI, responses were consistent, except BI5 (SD = 1.098), indicating a wider spread of opinions. All items showed negative skewness, suggesting a tendency toward higher-scale responses. Kurtosis values were within the acceptable range (±3), confirming normal distribution. Overall, the data demonstrates sufficient reliability and meet assumptions for parametric analysis.

Model and Structural Analysis

To test the study's hypotheses and examine variable relationships, Partial Least Squares Structural Equation Modelling (PLS-SEM) was employed. This method is appropriate for complex models with latent constructs, non-normal data and exploratory research contexts such as AI adoption in the public sector (Hair Jr. et al., 2021; Akter et al., 2017; Jain et al., 2022).

The reflective measurement model was evaluated for convergent validity, internal consistency, and discriminant validity. All outer loadings exceeded the 0.70 threshold, except for five low-loading Facilitating Conditions (FC) indicators, which were removed. This adjustment improved the Average Variance Extracted (AVE) from 0.494 to 0.689, thereby confirming convergent validity (Hair Jr. et al., 2021). Internal consistency was supported with Cronbach's alpha and composite reliability values above 0.70 for all constructs. Discriminant validity was established using Heterotrait–Monotrait ratio (HTMT), with all values below the 0.90 threshold.

Table 2. Measurement Model Analysis

Construct	α	rho_a	AVE	HTMT
Performance Expectancy	0.953	0.955	0.752	0.673
Effort Expectancy	0.932	0.937	0.787	0.621
Social Influence	0.932	0.933	0.678	0.514
Facilitating Conditions	0.850	0.850	0.689	0.572
Behavioural Intention	0.977	0.978	0.863	-

The structural model was assessed using path coefficients (β), t-values, p-values, adjusted R^2, and effect sizes (f^2). Bootstrapping with 5,000 subsamples confirmed that all four independent variables had significant positive effects on Behavioural Intention (BI) ($p < 0.001$). Performance Expectancy (PE) had the strongest effect ($\beta = 0.650$; $f^2 = 0.732$), followed by Effort Expectancy (EE) ($\beta = 0.599$; $f^2 = 0.560$), Facilitating Conditions (FC) ($\beta = 0.522$; $f^2 = 0.375$), and Social Influence (SI) ($\beta = 0.498$; $f^2 = 0.329$). All t-values exceeded 1.96, confirming statistical significance at the 5% level. Adjusted R^2 values showed that PE explained the most variance in BI (42.5%), followed by EE (35.7%), FC (27.1%), and SI (24.6%).

Table 3. Structural Model Analysis

Hyp	Relationship	β	t-statistic	p-value	Decision	R2	f2	Effect Size
H1	PE -> BI	0.650	7.997	0.000	Supported	0.425	0.732	Large
H2	EE -> BI	0.599	14.858	0.000	Supported	0.357	0.560	Large
H3	SI -> BI	0.498	4.615	0.000	Supported	0.246	0.329	Medium
H4	FC -> BI	0.522	12.487	0.000	Supported	0.271	0.375	Large

Moderation Analysis

AI Literacy was conceptualised as a reflective-reflective higher-order construct (HOC) comprising four lower-order dimensions namely Awareness, Usage, Evaluation and Ethics. Using the repeated indicator approach, this hierarchical component model (HCM) effectively captures the multidimensionality of AI Literacy while maintaining model parsimony (Sarstedt et al., 2022). Interaction effects between AI Literacy and each UTAUT variable of Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI) and Facilitating Conditions (FC) were tested. Only the interaction with SI (H7) was statistically significant ($\beta = -0.109$; $t = 2.513$; $p = 0.012$), indicating that AI Literacy significantly moderates the relationship between Social Influence and Behavioural Intention by reducing the influence of social pressure. The negative coefficient suggests that individuals with higher AI literacy are less influenced by social norms or pressure when adopting AI. In contrast, interaction terms for PE, EE and FC were not significant ($p > 0.05$) and showed negligible effect sizes ($f^2 < 0.02$), indicating no meaningful moderation. These findings underscore the selective moderating role of AI Literacy, while it does not significantly alter most UTAUT relationships, it meaningfully reduces reliance on external social cues in AI adoption decisions.

Table 4. Moderation Analysis

Hyp	Indirect Effect	β	t-statistic	p-value	Decision	R2	f2	Effect Size
H5	AI Lit x PE -> BI	-0.047	1.444	0.149	Not supported	0.588	0.008	Negligible
H6	AI Lit x EE -> BI	-0.039	1.111	0.267	Not Supported	0.512	0.005	Negligible
H7	AI Lit x SI -> BI	-0.109	2.513	0.012	Supported	0.546	0.028	Small
H8	AI Lit x FC -> BI	-0.058	1.766	0.077	Not supported	0.500	0.009	Negligible

DISCUSSION

This study examines behavioural intention to adopt AI in the Malaysian public sector, guided by the UTAUT model and moderated by AI Literacy. The findings offer both theoretical validation and practical insights into how key drivers of Performance Expectancy (PE), Effort Expectancy (EE), Facilitating Conditions (FC) and Social Influence (SI) interact with AI Literacy to shape adoption intentions.

Performance Expectancy emerged as the strongest predictor of AI adoption, aligning with UTAUT and prior research (Avci, 2022; Venkatesh et al., 2003). Managers are more inclined to adopt AI when they perceive it enhances efficiency, decision-making and policy execution, highlighting the need for AI initiatives to demonstrate tangible performance benefits. Effort Expectancy and Facilitating Conditions also showed significant effects, affirming that the ease of use and support infrastructure (e.g., training, resources, policy alignment) are critical enablers (Handayanto & Ambarwati, 2022; Radhakrishnan & Chattopadhyay, 2020). In a context where digital maturity varies, simplifying AI tools and ensuring technical support is vital for widespread adoption. While Social Influence had a weaker effect, likely due to the hierarchical and procedural structure of the public sector, the moderating role of AI Literacy was significant. Respondents with higher AI Literacy were less influenced by social norms, indicating greater autonomy in adoption decisions. This supports previous findings that AI-literate individuals engage more critically and independently with AI technologies (Celebi et al., 2023; Long & Magerko, 2020).

Modelled as a higher-order construct, AI Literacy encompasses awareness, usage, evaluation, and ethics (Wang, Rau & Yuan, 2022). The results affirm its conceptual richness and position AI Literacy as a foundational competency for thoughtful and responsible AI engagement—particularly important in public governance, where decisions carry broad societal implications.

To contextualise the findings, this study proposes an Actionable AI Framework (Figure 1), adapted from Yigitcanlar et al. (2021). At its core is Technology Readiness and Acceptance, represented by the four UTAUT constructs that shape behavioural intention. Moderating this layer is AI Literacy, which enhances informed, autonomous decision-making while reducing reliance on peer influence. Above these layers lies Policy and Regulation, highlighting the role of institutional governance in ensuring scalable, ethical AI integration. This multi-layered, theory-driven model maps the interdependencies across individual, organisational and policy levels that collectively aspires toward a dynamic and future-ready public sector.

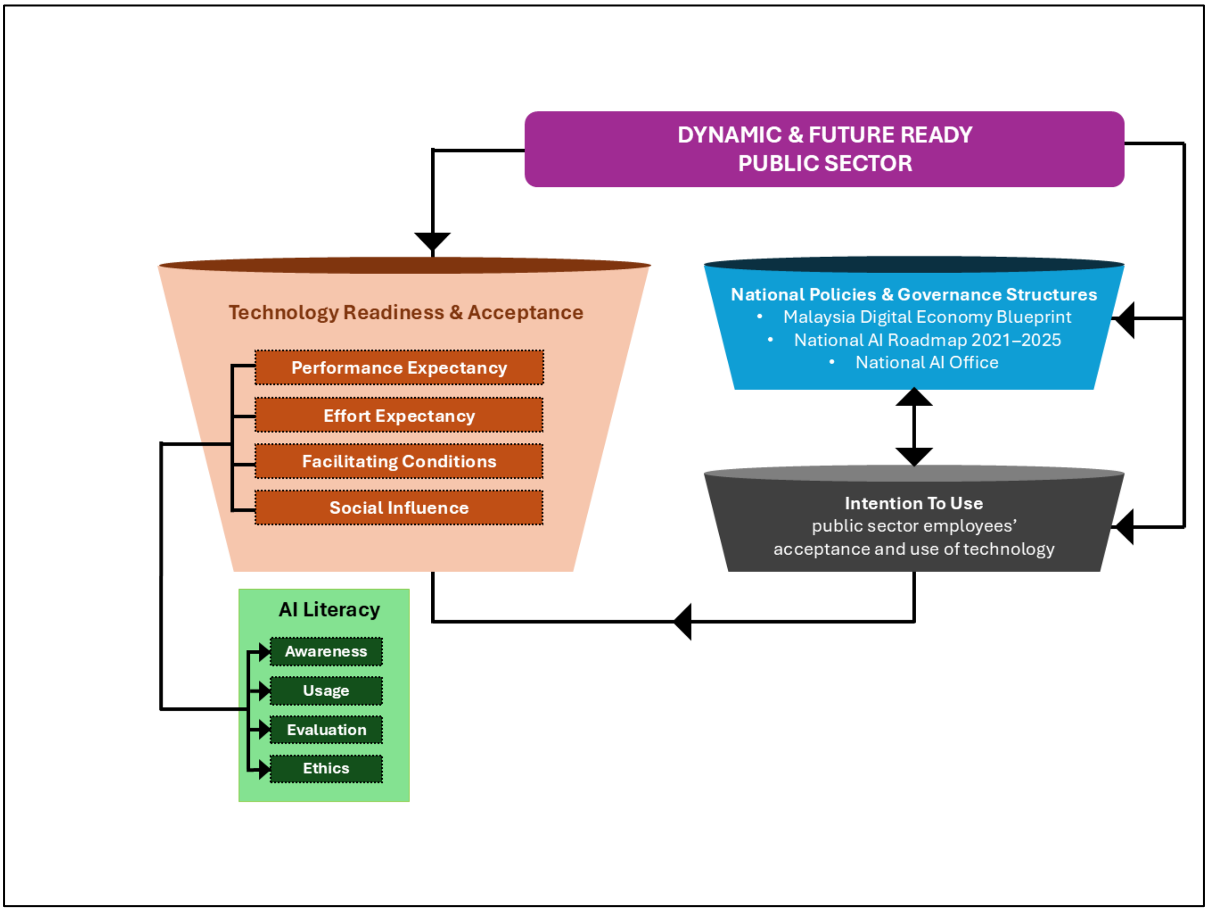

Figure 1. AI Adoption Framework

Dynamic & Future Ready Public Sector. At the top of the AI Framework is the aspiration to build a dynamic, innovation-driven, and future-ready public sector capable of navigating rapid technological and societal change. Achieving this requires a system-wide approach beginning with individual competencies, progressing through organisational readiness, and anchored by coherent national policies. Organisational agility is a key success factor, reflecting not just flexibility but also strategic foresight (Teece, 2018). This vision aligns with Malaysia's strategic agendas, including Malaysia MADANI, the

Public Sector Digitalisation Strategy and ASEAN's Digital Masterplan 2025, which aim to cultivate a public service that is efficient, innovative, and citizen-centric.

National Policies & Governance Structures. This vision is underpinned by national policies and governance structures that define the macro-environment for AI adoption. These frameworks offer strategic direction, mitigate risk and embed ethical standards. Key initiatives include MyDIGITAL, the National AI Roadmap (2021–2025) and the establishment of the National AI Office, all designed to drive public value through responsible AI use (Aziz, 2023). This layer also addresses trust, transparency and accountability, which are essential for addressing concerns around algorithmic bias, data privacy, and ethical risk (Floridi et al., 2018; Wachter et al., 2017). Malaysia's upcoming Public Sector AI Guidelines represent a critical step toward responsive, values-aligned governance.

Intention to Use. At the behavioural core is the intention to use AI, drawn from the UTAUT model, capturing individual readiness to adopt AI. The study confirms Performance Expectancy as the strongest predictor, underscoring the need to clearly communicate AI's value in improving efficiency, decision-making and service delivery (Avci, 2022). Intention is further shaped by organisational norms, infrastructure and perceived ease of use, reinforcing that adoption is both a personal and institutional outcome.

Technology Readiness & Acceptance. Feeding into intention are the UTAUT constructs namely Performance Expectancy, Effort Expectancy, Facilitating Conditions and Social Influence. These represent the critical success factors for AI adoption. As noted by Jöhnk et al. (2020), successful public sector transformation requires more than access to technology, it demands digital maturity, strategic alignment and integration with existing workflows. For AI to create value, it must be embedded seamlessly into daily operations.

AI Literacy. At the foundation is AI Literacy, modelled as a higher-order construct comprising Awareness, Usage, Evaluation and Ethics (Wang et al., 2023). This study highlights AI Literacy as a key enabler and significant moderator particularly reducing reliance on social influence, thereby promoting more autonomous and informed adoption decisions (Celebi et al., 2023). AI-literate individuals demonstrate greater critical engagement and ethical awareness, reinforcing the shift from compliance-driven to values-driven adoption. Initiatives like AI Untuk Rakyat and structured civil service training underscore the government's commitment to cultivating these competencies. Without AI literacy, even the best strategies risk failure due to lack of cognitive, practical or ethical readiness.

RECOMMENDATIONS

Based on the study's findings, several strategic recommendations are proposed to support effective and sustainable AI adoption within the Malaysian public sector and potentially across ASEAN. Firstly, the government must prioritise AI literacy for public managers, extending beyond technical skills to include ethical awareness, critical thinking and confident application in administrative contexts. Structured, role-based upskilling programmes that incorporate hands-on training and practical application are essential. Existing initiatives such as MyDIGITAL, AI Untuk Rakyat, and public-private partnerships (e.g. Microsoft's MyDIGITAL GovTech Innovation Partnership and Google's AI at Work 2.0) lay a strong foundation. Programmes led by the Public Service Department, such as the Competency Excellence initiative, also facilitate exposure to emerging technologies through training and international attachments. These efforts should be scaled and institutionalised to build a future-ready, AI-capable civil service.

Secondly, improving facilitating conditions is key. This includes access to reliable infrastructure, technical support and the establishment of agency-level AI support units or Centres of Excellence. The appointment of Chief Digital Officers (CDOs) under MyDIGITAL reflects this direction, promoting leadership in digital initiatives and fostering cross-agency collaboration. Access to toolkits, pilot environments and iterative experimentation can also drive a culture of innovation and lower adoption barriers. Thirdly, AI-related policies should move beyond strategy to include clear implementation frameworks, KPIs and operational guidelines aligned with real-world public sector workflows. Innovation incentives such as pilot grants, recognition schemes and cross-agency learning platforms can further motivate adoption. This aligns with Malaysia's Whole-of-Government approach, the Twelfth Malaysia Plan (RMKe-12), Malaysia MADANI and supports broader commitments to the UN Sustainable Development Goals (SDGs), particularly Goals 4, 9, and 16. Lastly, AI governance must prioritise transparency, accountability, fairness and data protection. These principles should be integrated into leadership development, procurement standards and civil service training. Malaysia's forthcoming Public Sector AI Adaptation Guidelines, developed by Jabatan Digital Negara and MOSTI, are intended to guide responsible implementation. Embedding these principles into everyday practice will reinforce public trust and ensure alignment with national values and global ethical standards.

CONCLUSION

This study provides key insights into AI adoption in Malaysia's public sector, highlighting the critical roles of performance expectancy, facilitating conditions, effort expectancy and social influence in shaping behavioural intention. AI literacy emerged as a strategic enabler by reducing the effect of social influence and promoting autonomous, informed decision-making. The proposed Actionable AI Framework offers a scalable, multi-level model linking individual readiness, organisational support and alignment with national digital policy serving as both a theoretical contribution and a practical tool for accelerating public sector AI readiness. Beyond Malaysia, these findings provide a regional roadmap for ASEAN Member States, supporting digital cohesion and enhancing governance capacity. Strengthening AI literacy, leadership, and institutional frameworks is essential to building a future-ready, ethical, and innovation-driven public sector.

ACKNOWLEDGEMENTS OR NOTES

Declaration of Generative AI and AI-assisted Technologies in the Writing Process

During the preparation of this work, the authors have used ChatGPT in order to assist in content clarity. After using this tool/service, the authors have reviewed and edited the content as needed and take full responsibility for the content of the publication.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

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