Teachers' Awareness of AI Tools and School Administration in Secondary Schools in Kuala Lumpur

Muhamad Firdhaus Shahrom[1]*, Helme Heli[2]

[1,2] Faculty of Education and Humanities, UNITAR International University, Petaling Jaya, Malaysia

***Corresponding author:**

DOI : https://doi.org/10.47772/IJRISS.2026.102400023

Received: 20 August 2026; Accepted: 25 August 2026; Published: 25 September 2026

ABSTRACT

Despite the current technological advancements in school administration, the lack of utilisation of ICT, and especially AI, highlights the need for teachers to increase productivity and efficiency in school management. This quantitative survey study aimed to investigate the level of teachers' awareness of AI tools for school administration in selected secondary schools in Kuala Lumpur. The study also sought to determine the factors influencing teachers' awareness and adoption of AI tools for school administration and to examine the relationship between teachers' awareness and factors influencing the adoption of AI tools for school administration. The study included 201 teachers from selected secondary schools in Kuala Lumpur as respondents, selected through stratified random sampling. The questionnaire for the study contained 40 Likert-scale items with 5 points, adapted from past research instruments. The reliability of the research instrument obtained a Cronbach's Alpha value, $\alpha = 0.93$, from pilot study data. The collected data underwent both descriptive and Pearson correlation data analysis. The results of the descriptive analysis showed that the average score for teachers' awareness was $x = 3.84$. Ten items for factors influencing teachers' awareness and adoption of AI tools for school administration received high average scores of $x = 3.86$. The Pearson correlation revealed a significant strong positive correlation ($r = 0.933$, $p < 0.001$) between teachers' awareness and factors influencing the adoption of AI tools for school administration. Therefore, applications of AI tools must be further expanded to encourage pro-AI practices among teachers, increasing the utilisation of ICT in schools.

Keywords: Artificial Intelligence (AI) Tools, School Administration, Teacher Awareness, Theory of Planned Behaviour (TPB), Technology Adoption, Secondary School Teachers

INTRODUCTION

The adoption of Artificial Intelligence (AI) in education has significantly transformed language teaching and learning by introducing innovative pedagogical approaches and technology-driven learning experiences (Chen et al., 2024; Fitria, 2021). Artificial intelligence (AI) is broadly defined as the science and engineering of developing intelligent computational systems capable of emulating human cognitive functions such as reasoning, learning, and autonomous decision-making (Manning, 2020). Through advanced machine learning and deep learning architectures, modern AI systems adapt to dynamic environments by operating across a dual framework of autonomy and performance (Gil de Zúñiga et al., 2024). Historically rooted in John McCarthy's foundational 1956 conceptualization following Alan Turing's legacy, AI has evolved beyond theoretical computation to become an integral component of Information and Communication Technology (ICT) ecosystems (Singh & Jain, 2018). Within the educational sector, the practical application of ICT has long supported core operational workflows, including data management, communication networks, administrative record-keeping, and e-learning platforms (Tahir et al., 2015). Today, the strategic integration of AI into these existing ICT infrastructures promises to optimize productivity and significantly elevate institutional efficiency on a global scale (Blaylock, 2019).

The operationalization of AI-driven ICT management fosters collaborative synergy among schools, parents, local authorities, and external organizations, thereby transforming institutional administration into an efficient, data-informed practice. However, integrating emerging technologies into routine educational management presents substantial pedagogical and systemic challenges. Educators frequently encounter barriers such as technological apprehension, institutional resistance to change, and insufficient specialized training (Dzemydienė et al., 2023). Also, AI systems assist educational administration by automating routine, labor-intensive tasks such as enrollment management and assessment grading. This reduces administrative workloads for non-academic personnel and allows institutional managers to concentrate on strategic operational priorities (Karim et al., 2024). While AI competencies are increasingly recognized as essential skill sets for educational personnel, systemic implementation requires robust policy frameworks and targeted capacity-building initiatives (Montagnier & Ek, 2021). Assessing educators' levels of technological comprehension serves as an essential mechanism for identifying adoption reluctance and formulating structured interventions to enhance institutional readiness (Alfaro-Ponce et al., 2023).

Despite the rapid modernization of educational management tools, significant operational deficiencies persist among administrative and instructional staff. In Malaysia, empirical evidence demonstrates that secondary school educators remain underprepared for the deployment of AI in administrative roles. Local research indicates that only 27% of urban Malaysian educators possess foundational awareness of AI applications within school administration, with most citing ambiguity regarding its practical execution (Ahmad et al., 2022). Furthermore, national EdTech assessments by the Ministry of Education reveal a critical deficit of AI-specific training modules within existing teacher professional development programs. Even in digitally equipped urban centers like Kuala Lumpur, technological integration remains uneven, driven by disparities in digital literacy, motivation, and practical ICT proficiency (Vakaliuk et al., 2021).

Addressing these empirical gaps requires active teacher engagement and structured investigation into the cognitive and behavioral constructs governing technology adoption (Yahya & Raman, 2020). Grounded in the conceptual framework (as illustrated in Figure 1) model outlined by Varpio et al. (2020) and informed by the Knowledge, Attitude, and Practice (KAP) model (Alea et al., 2020), this study assesses the relationship between teachers' core operational constructs (knowledge, attitude, and practice) as independent variables and their overall awareness and adoption readiness of AI administrative tools as the dependent variable. Specifically, this research investigates the current awareness levels among secondary school educators in Kuala Lumpur, identifies the critical determinants shaping AI adoption, and tests the null hypothesis regarding the relationship between teacher awareness and the underlying factors governing AI tool adoption in school administration.

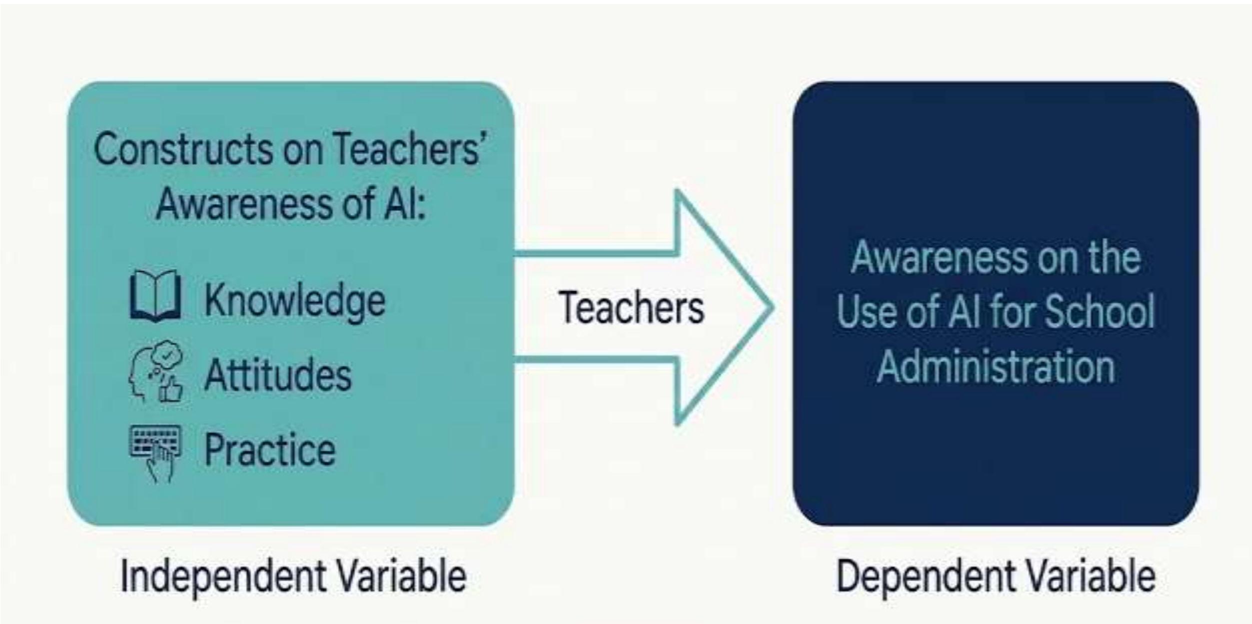

Figure 1. Conceptual Framework of the Study

LITERATURE REVIEW

Historical Foundations and Technological Evolution of AI

Artificial intelligence (AI) has evolved from early mechanical reasoning concepts and Alan Turing's computational theories into sophisticated modern architectures capable of emulating human cognition (Russell & Norvig, 2021). Formally inaugurated at the 1956 Dartmouth Conference by McCarthy, Minsky, Rochester, and Shannon, the discipline advanced from symbolic theorem-proving systems (Newell & Simon, 1956; McCorduck, 2004) to knowledge-based expert systems following historical "AI winters" (Russell & Norvig, 2021). Recent computational breakthroughs, big data availability, and deep learning architectures, most notably the transformer models introduced by Vaswani et al. (2017), have enabled scalable generative and administrative applications. In educational management, these tools increasingly streamline scheduling, data analysis, and workload distribution, necessitating structured professional development to build educator readiness (Zawacki-Richter et al., 2019).

Applications and Governance of AI in Educational Administration

In school management, artificial intelligence operationalises through several practical domains that directly alleviate routine administrative burdens. These technologies encompass automated scheduling systems that optimize class timetables and room allocations, AI-enhanced attendance and facial recognition platforms that monitor student absenteeism in real time, and predictive analytics dashboards within learning management systems (LMS) that aggregate academic indicators to detect at-risk learners early (Katsamakas et al., 2024; Wang, 2021). Besides, institutional governance in education increasingly relies on market-oriented managerialism and corporate structures to enforce public accountability (Chikuvadze et al., 2024). This indicates that the use of AI in educational administration is significantly important to maintain effective governance. Furthermore, generative AI tools such as large language models are increasingly leveraged by educators and department heads to draft institutional correspondence, summarize faculty meeting minutes, generate school activity reports, and streamline parent-teacher communications (Ghimire & Edwards, 2024; Sposato, 2025). By delegating repetitive, time-intensive documentation to intelligent systems, school personnel can redirect cognitive bandwidth toward strategic leadership and pedagogical mentoring (Wang, 2021).

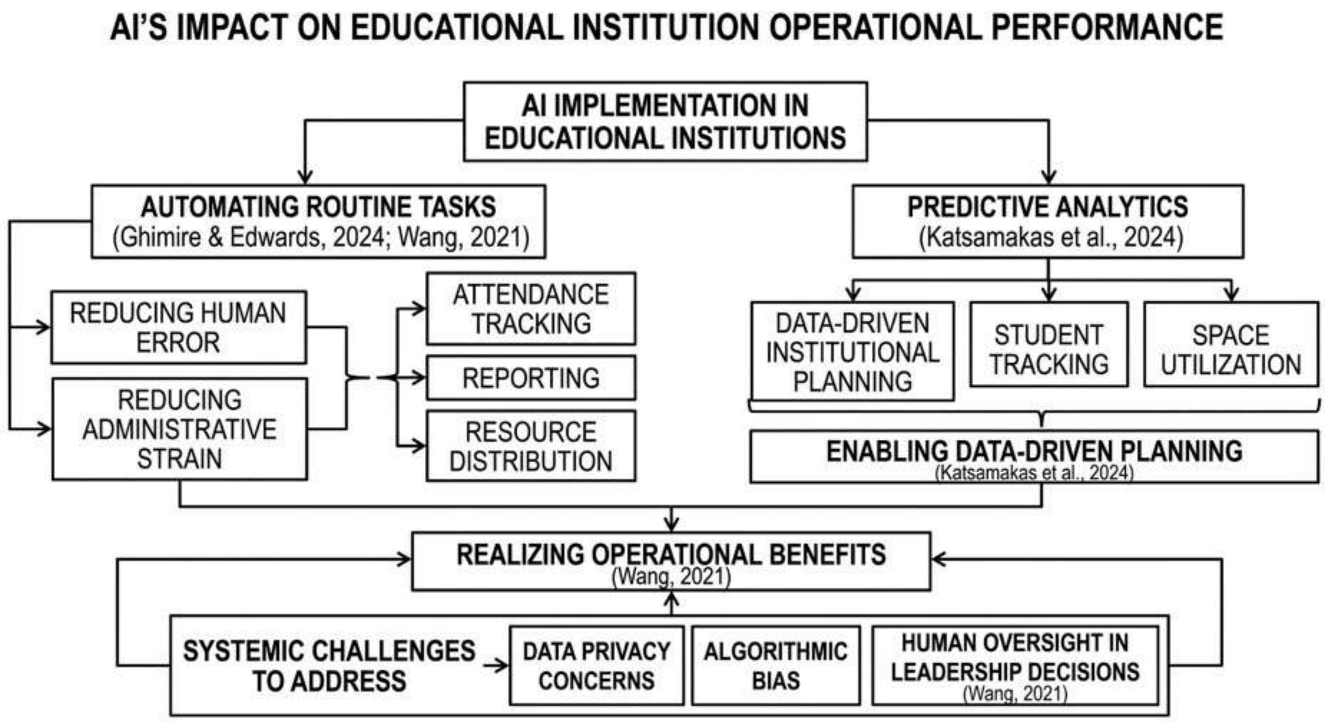

Figure 2: Application and Governance of AI in Educational Administration

Prior Empirical Studies, Survey Methodologies, and Research Gaps

Prior empirical research demonstrates that survey-based and mixed-method designs effectively assess

institutional readiness, user perceptions, and adoption patterns across diverse educational settings (Ghimire & Edwards, 2024; Katsamakas et al., 2024; Wang, 2021). Standardized surveys provide the scalability, cost-efficiency, and quantitative rigor needed to capture variations across teaching experience and technological exposure (Wang, 2021). Despite documented efficiencies, current literature reveals critical gaps: while higher education applications are widely documented (Ghimire & Edwards, 2024), secondary school environments remain under-researched regarding teacher awareness, workforce adaptation, policy development, and context-specific administrative tools (Katsamakas et al., 2024; Wang, 2021).

THEORETICAL FRAMEWORK

Theory of Planned Behavior (TPB)

To examine the determinants governing AI integration, this study adopts the Theory of Planned Behavior (Ajzen, 1991). The TPB posits that individual behavioral intention and subsequent actions are driven by three core constructs: attitude toward the behavior, subjective norms (perceived social expectations), and perceived behavioral control (perceived ease or difficulty of execution). Widely applied in educational technology research, the TPB provides a robust theoretical foundation for evaluating how secondary school educators' beliefs, institutional support systems, and perceived self-efficacy predict their intention and readiness to adopt AI tools for school administration.

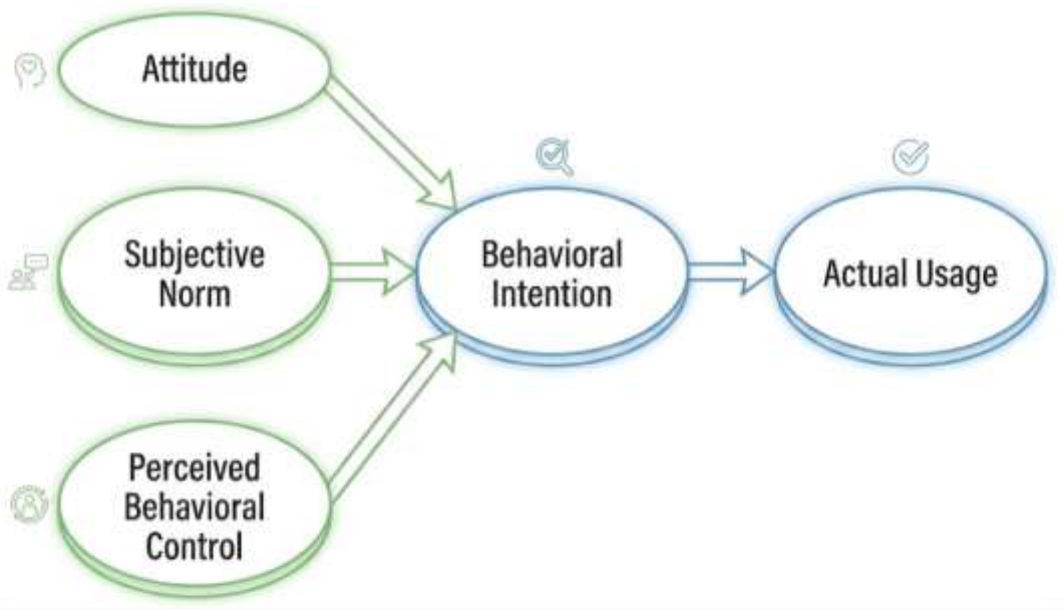

Figure 3. Theoretical Framework of the Study

METHODOLOGY

Research Design

This study employs a quantitative survey research design to investigate secondary school teachers' awareness, knowledge, attitudes, practices, and adoption factors regarding artificial intelligence (AI) like ChatGPT in school administration. A structured questionnaire hosted on Google Forms served as the primary instrument for empirical data collection. To optimize reach and response rates across secondary school educators, the digital survey was administered electronically through institutional and professional communication channels, specifically WhatsApp and Telegram.

Participants and Sampling

The study target population comprised national secondary school teachers under the Department of Education of the Federal Territory of Kuala Lumpur, with the accessible population delimited to educators administered by the Bangsar/Pudu District Education Office ($N = 419$). Utilizing a stratified random sampling strategy to ensure equitable subgroup representation, mitigate selection bias, and optimize resource efficiency (Thompson, 2012), the required sample size was determined using Krejcie and Morgan's (1970) sample size determination framework, yielding a final minimum sample requirement of 201 respondents.

Instrument and Data Collection

The adapted, expert-validated questionnaire comprises five distinct sections: Part A (demographics), Part B (knowledge of AI, 10 items), Part C (attitudes toward AI, 10 items), Part D (practices regarding AI, 10 items), and Part E (factors influencing awareness and adoption, 10 items), all scored on standard five-point Likert scales (agreement and frequency). Formal data collection followed hierarchical institutional clearance, obtaining approval from the Educational Planning and Research Division (EPRD/BPPDP) via eRAS 2.0 and the Kuala Lumpur State Education Department (JPWPKL). Pre-testing and instrument reliability were confirmed via Cronbach's alpha in a pilot study prior to full-scale electronic deployment.

Data Analysis

Data analysis is conducted using the Statistical Package for the Social Sciences (SPSS) Version 27.0 (Sadriddinovich, 2023). Descriptive statistics (frequencies, percentages, means, and standard deviations) assess baseline levels of knowledge, attitude, practice, and adoption factors. Prior to inferential testing, data normality is evaluated using skewness and kurtosis indices, applying the threshold criteria of -1.96 to $+1.96$ (Chua, 2013). Meeting univariate normality assumptions validates the use of the Pearson product-moment correlation coefficient to examine the strength and direction of the relationship between teachers' awareness and the determinants influencing their administrative adoption of AI (Schober et al., 2018).

The analytical scope of this study was intentionally delimited to examining overall construct distributions, regression dynamics, and correlational relationships across the primary variables. While subgroup inferential comparison, such as independent samples t-tests and one-way analyses of variance (ANOVA) across demographic variables like gender and academic qualification levels, remain viable avenues for broader exploration, the current investigation prioritized establishing baseline validity, composite awareness levels, and core structural relationships governing AI tool adoption.

RESULTS

Demographic Profile of Respondents

Table 1 summarised demography of the sample of this study which involved 201 teachers, namely male 68 teachers (33.8 %), and female 133 teachers (66.2 %). Furthermore, the academic qualifications respectively involved were Diploma, 23 teachers (11.4 %), Bachelor's Degree, 89 teachers (44.3 %), Master's Degree, 54 teachers (26.9 %), and PhD, 35 teachers (17.4 %).

Table 1. Demographic Profile of the Respondents (N=201) Demography of sample

Demography	Item	Frequency	Percentage	Total
Gender	Male	68	33.8 %	201 (100 %)
	Female	133	66.2 %	
Academic Qualifications	Diploma	23	11.4 %	
	Bachelor's Degree	89	44.3 %	

	Master's Degree	54	26.9 %	201 (100 %)
	PhD	35	17.4 %	

Descriptive Statistics of the Main Constructs

Table 2 illustrates the descriptive analysis of the main constructs that evaluate secondary school teachers' overall awareness and the influential factors governing the adoption of artificial intelligence (AI) tools in school administration across the sampled educators in Kuala Lumpur ($N = 201$). Interpreted using established mean score thresholds (Tschannen-Moran & Gareis, 2004) and standard deviation dispersion indices (Ruiz, 2002), the composite awareness construct, comprising Knowledge ($M = 3.86$, $SD = 0.77$), Attitude ($M = 3.85$, $SD = 0.78$), and Practice ($M = 3.81$, $SD = 0.81$) yielded an overall high level of awareness with an average mean score of 3.84 ($SD = 0.75$). Concurrently, the external and internal factors influencing AI awareness and adoption recorded a corresponding high level ($M = 3.86$, $SD = 0.77$), with individual item analysis indicating that institutional and governmental support ($M = 3.99$, $SD = 0.99$) and perceived tool accessibility ($M = 3.95$, $SD = 1.05$) serve as the strongest adoption drivers, while low standard deviations across all dimensions confirm the reliability and low dispersion of respondent ratings (Ruiz, 2002).

$N = 201$. Mean scores interpreted based on Tschannen-Moran and Gareis (2004): Low (1.81–2.60), Moderate (2.61–3.40), High (3.41–4.20), Very High (4.21–5.00). Standard deviation dispersion interpreted based on Ruiz (2002): Low Dispersion/Reliable (0.50–0.99).

Table 2. Descriptive Statistics of the Main Study Constructs

Construct	Number of Items	Mean (M)	Standard Deviation (SD)	Level / Interpretation
Knowledge	10	3.86	0.77	High
Attitude	10	3.85	0.78	High
Practice	10	3.81	0.81	High
Overall Awareness (Composite)	30	3.84	0.75	High
Adoption Factors	10	3.86	0.77	High

Reliability Analysis

Table 3 below shows the reliability analysis that evaluated the internal consistency of the survey instrument across its core constructs using Cronbach's alpha (α) coefficients derived from a pilot study conducted among secondary school teachers. Interpreted according to established benchmark standards (Adeniran, 2019; Amir et al., 2024), where $\alpha \geq 0.70$ signifies acceptable to high reliability and values approaching 1.0 denote robust internal consistency, the analysis yielded high reliability indices across all dimensions: Knowledge ($\alpha = 0.93$), Attitude ($\alpha = 0.82$), Practice ($\alpha = 0.98$), and Adoption Factors ($\alpha = 0.96$). With an overall composite reliability coefficient of $\alpha = 0.93$ across all 40 items, the instrument demonstrated excellent internal consistency, confirming its psychometric suitability and stability for full-scale data collection among the target educator population. Reliability interpretation based on Amir et al. (2024): Poor ($\alpha < 0.60$), Questionable ($0.60 \leq \alpha \leq 0.69$), Acceptable ($0.70 \leq \alpha \leq 0.79$), Good ($0.80 \leq \alpha \leq 0.89$), and Excellent ($\alpha > 0.90$); threshold criteria supported by Adeniran (2019).

Table 3. Reliability Analysis of the Questionnaire Subscales

No.	Construct	Number of Items	Cronbach's Alpha (α)	Interpretation / Internal Consistency
1.	Knowledge	10	0.93	Excellent
2.	Attitude	10	0.82	Good

3.	Practice	10	0.98	Excellent
4.	Factor (Adoption Influences)	10	0.96	Excellent
	Total Scale	**40**	**0.93**	**Excellent**

Normality Analysis

To assess whether the data satisfied the parametric assumptions required for subsequent inferential statistical

procedures, a univariate normality analysis was performed using skewness and kurtosis indices for the primary study variables ($N = 201$) which is shown in table 4. According to the statistical guidelines established by Chua (2013), data distribution is considered normally distributed when both skewness and kurtosis statistical values fall within the acceptable threshold range of -1.96 to $+1.96$. The analysis demonstrated that the composite variable of teachers' awareness of AI tools exhibited a skewness value of -0.300 and a kurtosis value of -1.683, while the factors influencing AI adoption recorded a skewness value of -0.407 and a kurtosis value of -1.419. Because all observed coefficients reside strictly within the permissible critical bounds of ± 1.96, the dataset satisfies the assumption of normality, thereby validating the application of parametric tests of specifically the Pearson product-moment correlation analysis to evaluate the relationships between the constructs (Chua, 2013; Schober et al., 2018).

Table 4. Tests of Normality for the Principal Variables

No.	Construct / Variable	Skewness	Kurtosis	Threshold Range	Distribution Status
1.	Teachers' Awareness of AI Tools	-0.300	-1.683	-1.96 to $+1.96$	Normally Distributed
2.	Factors Influencing AI Adoption	-0.407	-1.419	-1.96 to $+1.96$	Normally Distributed

Correlation Analysis Between Teacher Awareness and Adoption Factors

In Table 5, a Pearson product-moment correlation analysis was conducted to test the null hypothesis (H_0), which posited no significant relationship between secondary school teachers' awareness of artificial intelligence (AI) tools and the factors influencing their adoption for school administration ($N = 201$). Evaluated against the correlation coefficient interpretation criteria established by Schober et al. (2018), the analysis revealed a statistically significant, very strong positive relationship between teachers' awareness and adoption factors, $r(199) = 0.933$, $p < .001$. Consequently, the null hypothesis (H_0) was rejected, demonstrating that higher awareness, encompassing knowledge, attitudes, and practical engagement, is directly associated with a stronger influence of facilitating adoption factors, such as institutional readiness, government initiatives, and perceived usefulness (Güneyli et al., 2024; Hazzan-Bishara et al., 2025; Schober et al., 2018).

Table 5. Pearson Correlation Analysis Between Teacher Awareness and Adoption Factors ($N = 201$)

Variable	Statistical Metric	Factors Influencing AI Adoption	Hypothesis Decision (H0)
Teachers' Awareness of AI Tools	Pearson Correlation (r)	0.933^{**}	Reject H_0
	Sig. (2-tailed), p-value	$< .001$	
	Sample Size (N)	201	

$p < .001$ (2-tailed). Correlation strength interpreted based on Schober et al. (2018): Negligible (0.00–0.10), Weak (0.10–0.39), Moderate (0.40–0.69), Strong (0.70–0.89), and Very Strong (0.90–1.00).

Linear Regression Analysis of Predictors Influencing AI Adoption

A simple linear regression analysis (as shown in Table 6) was conducted to determine the extent to which secondary school teachers' overall awareness of artificial intelligence (AI) tools predicts the factors influencing their adoption for administrative tasks ($N = 201$). The regression model demonstrated statistical significance, $F(1,199) = 1335.79, p < .001$, accounting for 87.0% of the variance in adoption factors ($R^2 = .870$, adjusted $R^2 = .870$). Teachers' awareness significantly and positively predicted adoption factors ($\beta = 0.933, B = 0.957, SE = 0.026, t = 36.55, p < .001$), establishing that for every one-unit increase in teacher awareness, adoption readiness increases by 0.957 units. These findings align with empirical models indicating that foundational awareness, practical knowledge, and positive attitudes serve as robust direct predictors of technology adoption and perceived administrative utility in educational settings (Güneyli et al., 2024; Hazzan-Bishara et al., 2025).

Table 6. Linear Regression Analysis: Teacher Awareness Predicting Adoption Factors ($N = 201$)

Model / Predictor Variable	B	SE	β	t	p-value	R	R2	Adjusted R2	F(1,199)
(Constant)	0.185	0.101	-	1.83	.069				
Teachers' Awareness of AI Tools	0.957	0.026	0.933	36.55	< .001	.933	.870	.870	1335.79^{***}

DISCUSSION

Current Level of Teachers' Awareness of AI Tools (Research Question 1)

The findings directly address the first research question by establishing that secondary school educators in Kuala Lumpur demonstrate an overall high level of awareness regarding artificial intelligence (AI) tools in school administration, with a composite mean score of 3.84 ($SD = 0.75$). Evaluated through the conceptual framework comprising knowledge, attitude, and practice, high awareness levels were consistently observed across all three dimensions. In the knowledge domain ($M = 3.86, SD = 0.77$), educators demonstrated strong comprehension of the operational benefits and data security implications of AI (Items B6 and B10). This finding corroborates Chai et al. (2021) and Ng et al. (2022), who observed that educators in technologically advanced urban regions exhibit rising awareness driven by national initiatives like the Malaysia Education Blueprint. However, the lower self-efficacy recorded for technical implementation requirements (Item B5) aligns with Sanusi et al. (2024), indicating that while foundational conceptual knowledge is present, deeper technical deployment skills remain limited without structured institutional support. Regarding attitudes ($M = 3.85, SD = 0.78$), teachers exhibited high willingness and confidence in utilizing AI for administrative duties (Items C2 and C5). This finding resonates with Ahmad et al. (2022) and UNESCO (2022), who highlighted educator optimism regarding AI's capacity to alleviate administrative burdens. Finally, the practice dimension ($M = 3.81,\ SD = 0.81$) demonstrated proactive behavioral engagement, as teachers actively track technological challenges and monitor updates (Items D7 and D9). These practical behaviors support Lu et al. (2024) and Sposato (2025), who found that structured exposure and hands-on practice enhance perceived behavioral control and workflow efficiency.

Factors Influencing the Awareness and Adoption of AI Tools (Research Question 2)

The findings resolve the second research question by identifying both internal and external determinants that shape teachers' awareness and administrative adoption of AI tools, recording an overall high level ($M = 3.86$, $SD = 0.77$). Among the evaluated determinants, institutional and systemic factors emerged as the strongest catalysts. Government initiatives and assistance (Item E2, $M = 3.99$) alongside perceived accessibility of AI technologies (Item E7, $M = 3.95$) attained the highest agreement levels. These results support Ivanov et al. (2024), who emphasized that systemic institutional training and policy support significantly increase educators' perceived behavioral control and administrative adoption rates. Furthermore, the findings reflect the conclusions of Hazzan-Bishara et al. (2025), who demonstrated that tool accessibility and exposure serve as core predictors of technology adoption. Conversely, peer participation and perceived reliability (Items E6 and E10) received lower relative ratings. This discrepancy indicates that educators approach administrative technology integration through individual initiative and formal organizational mandates rather than peer influence alone, reinforcing Hazzan-Bishara et al.'s (2025) and Ivanov et al.'s (2024) observations that structured organizational governance is essential to overcome skepticism regarding tool reliability.

The Impact of Teacher Awareness on AI Tool Adoption (Research Question 3)

Addressing the third research question, the inferential analysis confirms that teachers' awareness of AI tools significantly and positively impacts their ability and willingness to adopt these technologies for administrative tasks. Pearson correlation analysis revealed a statistically significant, very strong positive relationship between teachers' awareness and adoption factors, $r(199) = 0.933$, $p < .001$, leading to the rejection of the null hypothesis (H_0). Based on the interpretative benchmarks of Schober et al. (2018), this strong association demonstrates that elevated awareness, developed through knowledge, positive attitudes, and habituated practice, directly strengthens educators' responsiveness to adoption drivers. These results align with Güneyli et al. (2024), who established that foundational AI awareness and institutional facilitation directly enhance adoption likelihood in educational environments. Additionally, the findings validate the theoretical framework of the Theory of Planned Behavior (Ajzen, 1991) and the extended Technology Acceptance Model (Hazzan-Bishara et al., 2025), where awareness acts as a foundational precursor that amplifies perceived usefulness, perceived behavioral control, and behavioral intention. Consequently, increasing comprehensive teacher awareness serves as a direct operational prerequisite for successful and sustainable AI integration across secondary school management.

Theoretical Implications

The empirical findings of this study offer significant theoretical contributions to the literature on educational technology adoption by substantiating and refining the Theory of Planned Behavior (Ajzen, 1991) within the domain of educational management. By conceptualizing awareness through the integrated dimensions of knowledge, attitude, and practice, the results demonstrate that multi-dimensional awareness acts as a foundational precursor that directly governs educators' perceived behavioral control and adoption intentions. The observed very strong correlation between awareness and adoption determinants ($r = 0.933, p < .001$) further corroborates extended Technology Acceptance Models (TAM), aligning with Hazzan-Bishara et al. (2025) and Güneyli et al. (2024) in confirming that cognitive familiarity and constructive attitudes strongly amplify perceived administrative utility. Moreover, these findings reinforce Sanusi et al.'s (2024) theoretical assertions by illustrating that foundational AI knowledge is not merely an isolated variable, but an indispensable antecedent that directly predict teachers' willingness to transition from passive acceptance to sustained operational behavior.

Practical Implications

From a practical perspective, the findings provide educational policymakers and institutional leaders with actionable insights for optimizing AI integration across school administration. The elevated impact of government assistance ($M = 3.99$) and perceived tool accessibility ($M = 3.95$) emphasizes that systemic policy frameworks and structured infrastructure are critical catalysts for institutional readiness, supporting the recommendations of Ivanov et al. (2024) and UNESCO (2022) regarding national AI literacy initiatives. However, the lower self-efficacy reported in technical deployment (Item B5) indicates that school administrators must shift professional development from generic orientation toward hands-on, practical modules. Equipping educators with targeted competencies in automated record-keeping, scheduling, and data analytics can directly alleviate administrative workloads, thereby mitigating early career burnout and digital resistance (Idris, 2024; Lu et al., 2024; Sposato, 2025). Finally, addressing teachers' hesitations regarding data security and system reliability requires school leadership to establish transparent governance protocols, data privacy safeguards, and ethical oversight to ensure the responsible and sustainable implementation of AI tools in secondary schools (Ghimire & Edwards, 2024; Wang, 2021).

LIMITATION AND FUTURE RESEARCH DIRECTION

Several methodological limitations must be acknowledged when interpreting these findings. The empirical sample was delimited to secondary school educators within the Bangsar and Pudu districts of the Federal Territory of Kuala Lumpur, representing an urban cohort with comparatively mature digital infrastructure and systemic access. Consequently, the high levels of awareness observed may not reflect conditions across rural, semi-urban, or under-resourced schools. Future research should undertake replication studies across diverse Malaysian states, including suburban and rural communities in Sabah, Sarawak, Kedah, and Kelantan, to examine potential digital divides and infrastructure-driven variations in AI adoption readiness. Furthermore, because this study relied exclusively on a quantitative survey design, future studies should adopt mixed-methods approaches incorporating qualitative semi-structured interviews or focus group discussions with teachers and school principals. Qualitative inquiry will help unpack nuanced psychological resistance, organizational inertia, ethical reservations, and ground-level cultural barriers that standard Likert scales cannot fully capture. Future research should also conduct inferential subgroup analyses across demographic variables, including teaching experience cohorts, gender, and academic qualifications, to identify specific disparities in baseline awareness and adoption readiness."

CONCLUSION

This study investigated the awareness and adoption of artificial intelligence (AI) tools in school administration among 201 secondary school teachers across seven national schools in Kuala Lumpur. Overall, the educators demonstrated a high level of awareness across the 30 assessed items spanning knowledge, attitude, and practice, while the 10 evaluated adoption factors also recorded a high level of influence. The empirical findings confirmed a strong, positive connection between teacher awareness and the underlying drivers of technology adoption. These results indicate that when teachers possess a solid understanding, positive attitudes, and regular engagement with AI tools, their receptiveness to administrative adoption increases substantially. Although focused on secondary schools within the Bangsar and Pudu districts, this research underscores the critical need for structured AI literacy programs, accessible digital tools, and supportive institutional policies to advance digital transformation in school management.

ACKNOWLEDGEMENTS

The authors would love to thank UNITAR for the assistance provided to make this study possible and to the teachers who participated in this study.

REFERENCES

1. Adeniran, A. O. (2019). Application of Likert scale's type and Cronbach's alpha analysis in an airport perception study. Scholar Journal of Applied Sciences and Research, 2(4), 1–5.
2. Ahmad, S. F., Alam, M. M., Rahmat, M. K., Mubarik, M. S., & Hyder, S. I. (2022). Academic and administrative role of artificial intelligence in education. Sustainability, 14(3), Article 1101. https://doi.org/10.3390/su14031101
3. Ajzen, I. (1991). The theory of planned behavior. Organizational Behavior and Human Decision Processes, 50(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T
4. Alea, L. A., Fabrea, M. F., Roldan, R. D. A., & Farooqi, A. Z. (2020). Teachers' COVID-19 awareness, distance learning education experiences and perceptions towards institutional readiness and challenges. International Journal of Learning, Teaching and Educational Research, 19(6), 127–144. https://doi.org/10.26803/ijlter.19.6.8
5. Alfaro-Ponce, B., Alfaro-Ponce, M., Muñoz-Ibáñez, C. A., Durán-González, R. E., Sanabria-Zepeda, J. C., & González-Gómez, Z. L. (2023). Education in Mexico and technological public policy for developing complex thinking in the digital era: A model for technology management. Journal of Innovation & Knowledge, 8(4), Article 100439. https://doi.org/10.1016/j.jik.2023.100439
6. Amir, S. S., Hashim, S. R. M., & Abdullah, K. (2024). Kesahan dan Kebolehpercayaan Instrumen Kebimbangan Matematik Sekolah Rendah. Jurnal Pemikir Pendidikan, 12(1).

7. Blaylock, J. (2019, December 29). The top five changes that occur with AI in education. Analytics Insight.
8. Chai, C. S., Lin, P. Y., Jong, M. S. Y., Dai, Y., Chiu, T. K., & Huang, B. (2021). Perceptions of and behavioral intentions towards learning artificial intelligence in primary school students. Educational Technology & Society, 24(3), 89–101.
9. Chen, X., Zou, D., Xie, H., Cheng, G., & Liu, C. (2024). Two decades of artificial intelligence in education: Contributors, collaborations, research topics, challenges, and future directions. Educational Technology & Society, 27(1), 28–47. https://doi.org/10.30191/ETS.202401_27(1).0003
10. Chikuvadze, P., Zuva, J., & Mugijima, S. (2024). Influence of the institutional governance model on the internationalisation of higher education in South Africa. Asian Journal of Social Science Research, 6(1), 1–11. https://doi.org/10.5281/zenodo.12702819
11. Chua, Y. P. (2013). Kaedah dan statistik penyelidikan: Buku 3 - Asas statistik penyelidikan: Analisis data skala Likert (Edisi ke-2). McGraw-Hill Education.
12. Dzemydienė, D., Turskienė, S., & Šileikienė, I. (2023). Development of ICT infrastructure management services for optimization of administration of educational institution activities by using ITIL-v4. Baltic Journal of Modern Computing, 11(4), 558–579. https://doi.org/10.22364/bjmc.2023.11.4.05
13. Fitria, T. N. (2021). Grammarly as AI-powered English writing assistant: Students' alternative for writing English. Metathesis: Journal of English Language, Literature, and Teaching, 5(1), 65–78. https://doi.org/10.31002/metathesis.v5i1.3519
14. Ghimire, A., & Edwards, J. (2024). From guidelines to governance: A study of AI policies in education.
15. Gil de Zúñiga, H., Goyanes, M., & Durotoye, T. (2024). A scholarly definition of artificial intelligence (AI): Advancing AI as a conceptual framework in communication research. Political Communication, 41(2), 317–334. https://doi.org/10.1080/10584609.2023.2297241
16. Güneyli, A., Burgul, N. S., Dericioğlu, S., Cenkova, N., Becan, S., Şimşek, Ş. E., & Güneralp, H. (2024). Exploring teacher awareness of artificial intelligence in education: A case study from Northern Cyprus. European Journal of Investigation in Health, Psychology and Education, 14(8), Article 2358. https://doi.org/10.3390/ejihpe140802358
17. Hazzan-Bishara, A., Kol, O., & Levy, S. (2025). The factors affecting teachers' adoption of AI technologies: A unified model of external and internal determinants. Education and Information Technologies, 1–27. https://doi.org/10.1007/s10639-024-13197-y
18. Idris, R. (2024, March 2). Gagal adaptasi sistem digital antara punca guru bersara awal. Berita Harian. https://www.bharian.com.my/berita/nasional/2024/03/1218689/gagal-adaptasi-sistem-digital-antara-punca-guru-bersara-awal
19. Ivanov, S., Soliman, M., Tuomi, A., Alkathiri, N. A., & Al-Alawi, A. N. (2024). Drivers of generative AI adoption in higher education through the lens of the Theory of Planned Behaviour. Technology in Society, 77, Article 102521. https://doi.org/10.1016/j.techsoc.2024.102521
20. Karim, H. H., Hamid, N. B. A., & Rus, M. F. C. (2024). Exploring the impact and challenges of using artificial intelligence in an open, distance and digital education university: A conceptual paper. Asian Journal of Social Science Research, 6(2), 40–57. https://doi.org/10.5281/zenodo.14580204
21. Katsamakas, E., Pavlov, O. V., & Saklad, R. (2024). Artificial intelligence and the transformation of higher education institutions.
22. Krejcie, R. V., & Morgan, D. W. (1970). Determining sample size for research activities. Educational and Psychological Measurement, 30(3), 607–610. https://doi.org/10.1177/001316447003000308
23. Lu, H., He, L., Yu, H., Pan, T., & Fu, K. (2024). A study on teachers' willingness to use generative AI technology and its influencing factors: Based on an integrated model. Sustainability, 16(16), Article 7216. https://doi.org/10.3390/su16167216
24. Manning, C. (2020). Artificial intelligence definitions. Stanford University, Human-Centered Artificial Intelligence (HAI).
25. McCorduck, P. (2004). Machines who think: A personal inquiry into the history and prospects of artificial intelligence (2nd ed.). A K Peters/CRC Press.
26. Montagnier, P., & Ek, I. (2021). AI measurement in ICT usage surveys: A review (OECD Digital Economy Papers No. 308). OECD Publishing. https://doi.org/10.1787/2efbe16c-en

27. Newell, A., & Simon, H. A. (1956). The logic theory machine: A complex information processing system. IRE Transactions on Information Theory, 2(3), 61–79. https://doi.org/10.1109/TIT.1956.1056797
28. Ng, D. T. K., Leung, J. K. L., Chu, S. K. W., & Qiao, M. S. (2022). Conceptualizing AI literacy: An exploratory review. Computers and Education: Artificial Intelligence, 2, Article 100041. https://doi.org/10.1016/j.caeai.2021.100041
29. Ruiz, C. (2002). Instrumentos de investigación educativa: Procedimientos para su diseño y validación (1ª ed.). CIDEG.; 2002. 266 p.
30. Russell, S. J., & Norvig, P. (2021). Artificial intelligence: A modern approach (4th ed.). Pearson.
31. Sadriddinovich, J. T. (2023). Capabilities of SPSS software in high volume data processing testing. American Journal of Public Diplomacy and International Studies, 1(9), 82–86.
32. Sanusi, I. T., Ayanwale, M. A., & Tolorunleke, A. E. (2024). Investigating pre-service teachers' artificial intelligence perception from the perspective of planned behavior theory. Computers and Education: Artificial Intelligence, 6, Article 100202. https://doi.org/10.1016/j.caeai.2024.100202
33. Schober, P., Boer, C., & Schwarte, L. A. (2018). Correlation coefficients: Appropriate use and interpretation. Anesthesia & Analgesia, 126(5), 1763–1768. https://doi.org/10.1213/ANE.0000000000002864
34. Singh, N. C., & Jain, R. (2018). "Personalising 'learning', Can AI promise customised education for humanity?" The Blue Dot, (9), 32–37.
35. Sposato, M. (2025). Artificial intelligence in educational leadership: A comprehensive taxonomy and future directions. International Journal of Educational Technology in Higher Education, 22(1), Article 20. https://doi.org/10.1186/s41239-024-00499-1
36. Tahir, L. M., Ali, M. F., Mohd Said, M. N. H., & Megat Zakaria, M. A. Z. (2015). ICT literacy and readiness in using computers among headteachers in their tertiary learning experiences and school management tasks. International Journal of Emerging Technologies in Learning, 10(2), 20–29. https://doi.org/10.3991/ijet.v10i2.4287
37. Thompson, S. K. (2012). Sampling (3rd ed.). John Wiley & Sons.
38. Tschannen-Moran, M., & Gareis, C. R. (2004). Principals' sense of efficacy: Assessing a promising construct. Journal of Educational Administration, 42(5), 573–585. https://doi.org/10.1108/09578230410554070
39. UNESCO. (2022). K-12 AI curricula: A mapping of government-endorsed AI curricula. UNESCO Publishing.
40. Vakaliuk, T., Novitska, I., Verbovsky, I., Rozhnova, T., & Kontsedailo, V. (2021). Management of educational institutions with inclusive education based on innovative technologies. SHS Web of Conferences, 104, Article 03008. https://doi.org/10.1051/shsconf/202110403008
41. Varpio, L., Paradis, E., Uijtdehaage, S., & Young, M. (2020). The distinctions between theory, theoretical framework, and conceptual framework. Academic Medicine, 95(7), 989–994. https://doi.org/10.1097/ACM.0000000000003075
42. Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, Ł., & Polosukhin, I. (2017). Attention is all you need. In I. Guyon, U. V. Luxburg, S. Bengio, H. Wallach, R. Fergus, S. Vishwanathan, & R. Garnett (Eds.), Advances in Neural Information Processing Systems (Vol. 30, pp. 5998–6008). Curran Associates, Inc.
43. Wang, Y. (2021). Artificial intelligence in educational leadership: A symbiotic role of human-artificial intelligence decision-making. Journal of Educational Administration, 59(3), 256–270. https://doi.org/10.1108/JEA-08-2020-0174
44. Yahya, Z., & Raman, A. (2020). Teachers' acceptance and challenges on technology use in secondary schools. South Asian Research Journal of Humanities and Social Sciences, 2(2), 133–142. https://doi.org/10.36346/sarjhss.2020.v02i02.008
45. Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education – where are the educators? International Journal of Educational Technology in Higher Education, 16(1), Article 39. https://doi.org/10.1186/s41239-019-0171-0