Impact of Artificial Intelligence Tools on Students Learning Outcomes and Skills Development

Ahmad Hafizin Azman Hashim, DianaRose Faizal[*], Nur Erma Suryani Mohd Jamel

Fakulti Pengurusan Teknologi dan Teknousahawanan, Universiti Teknikal Malaysia Melaka, Jalan TU 62, 75450 Ayer Keroh Melaka, Malaysia

***Corresponding Author**

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ABSTRACT

This study investigates the impact of artificial intelligence (AI) tools in the education sector, with a focus on their influence on students' learning outcomes and skill development in Malaysia. While AI offers potential benefits such as personalized learning, real-time feedback, and adaptive learning environments, its adoption remains limited due to a lack of awareness and understanding among educators and students. Using quantitative methods such as questionnaires, this research explores the factors motivating users in Malacca to utilize AI tools for educational purposes, examining aspects including technological adoption, access to AI systems, perceived utility, and ease of use. The findings are expected to address current gaps in public knowledge, highlight reasons for adopting AI in education, and evaluate its advantages, including advancing educational technology, expanding access to high-quality education through personalized learning, and enhancing outcomes and skill development via adaptive systems and real-time analytics. The study also acknowledges its limitation in focusing exclusively on Malaysia and suggests that similar studies in other countries could provide a more comprehensive understanding of AI's global potential in education, thereby emphasizing the importance of closing the knowledge gap and recognizing the transformative role of AI in advancing education.

Keywords: Artificial Intelligence, Education, Technology, Learning Outcomes

INTRODUCTION

The integration of Artificial Intelligence (AI) tools into educational settings has significantly transformed students' learning experiences, offering innovative ways for both students and educators to engage with content and processes. AI technology facilitates personalized learning, automates administrative tasks, and provides intelligent tutoring systems that adapt to individual student needs, thereby enhancing learning outcomes and skill development (Chen, Chen, & Lin, 2020). This technology is particularly valuable in education, where adaptive learning and real-time feedback can improve student achievement and engagement. In recent years, educational institutions worldwide have increasingly adopted AI tools, driven by their potential to provide tailored educational experiences, streamline administrative functions, and support data-driven decision-making. According to Holmes, Bialik, and Fadel (2020), the use of AI in education is projected to grow substantially, underscoring the increasing relevance of this technology in improving both educational outcomes and operational efficiency.

Despite these advancements, there remains a notable gap in empirical research regarding the impact of AI on students' learning outcomes and skill development, particularly within educational institutions in Melaka, Malaysia. While previous studies highlight AI's potential to enhance engagement and adaptive learning experiences (Williamson & Eynon, 2023), the specific factors that contribute to its effectiveness in transforming educational practices and outcomes in this local context remain underexplored.

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AI applications in education offer several advantages, such as personalized learning pathways, immediate feedback, and enhanced engagement through interactive environments. Intelligent tutoring systems, for example, can tailor educational content to students' individual learning styles and pace, thereby reducing learning gaps and improving academic performance. Furthermore, AI can provide educators and administrators with valuable insights into student performance and behavior, enabling them to refine instructional strategies and support services (Kautz et al., 2021). However, challenges such as over-reliance on AI, risks to creativity and critical thinking, academic integrity issues, and data privacy concerns (Wogu et al., 2018; Luan, 2020; Eloundou, 2023) must also be addressed to ensure effective and ethical integration. Given these opportunities and challenges, this study aims to examine the impact of AI tools on students' learning outcomes and skill development in educational institutions.

LITERATURE REVIEW

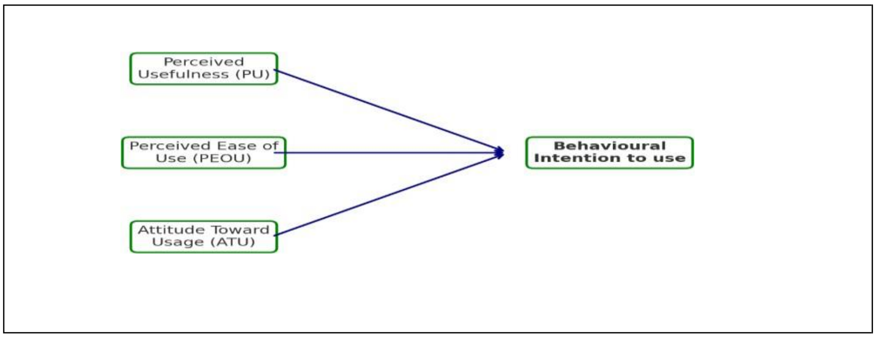
Artificial Intelligence (AI) is a field of study focused on developing systems capable of simulating human intelligence to perform tasks such as reasoning, problem-solving, perception, and natural language understanding (Russell & Norvig, 2011). AI encompasses various subfields, including Machine Learning (ML), which enables systems to learn and improve performance from data without explicit programming. Applications such as recommendation algorithms and fraud detection illustrate AI's broad potential across domains (Goodfellow, Bengio, & Courville, 2016).

AI technologies have become increasingly integrated into education, offering personalized learning pathways, adaptive content delivery, and intelligent tutoring systems that respond to student needs (Luckin et al., 2019). These systems improve engagement, reduce learning gaps, and enhance academic performance (Chen, Chen, & Lin, 2020). AI also supports educators through real-time analytics and data-driven insights, allowing for more effective instructional design and decision-making (Kautz et al., 2021). However, challenges such as data privacy, the digital divide, and insufficient teacher training limit the full potential of AI adoption (Williamson & Eynon, 2023).

AI has been shown to improve measurable learning outcomes, particularly in mathematics and science (Johnson & Matthews, 2022). Learning outcomes refer to the knowledge, skills, and attitudes students are expected to acquire, both academic (e.g., subject mastery) and non-academic (e.g., problem-solving and critical thinking) (Chen, Chen, & Lin, 2020). Beyond academics, AI also supports skill development by fostering creativity, teamwork, resilience, and analytical abilities (Eum et al., 2021). The Technology Acceptance Model (TAM) (Davis, 1989) is widely applied to study technology adoption in education. It emphasizes two constructs: Perceived Usefulness (PU) and Perceived Ease of Use (PEOU), which influence users' attitudes and behavioral intentions to adopt AI tools. Research highlights that when AI is perceived as beneficial and easy to use, students are more likely to adopt and integrate it into their learning (Holmes, Bialik, & Fadel, 2019). Extending TAM, the Technology-Organization-Environment (TOE) framework adds contextual factors such as institutional support, infrastructure, and external pressures, providing a holistic view of AI adoption in educational settings (Na et al., 2022).

CONCEPTUAL FRAMEWORK AND HYPOTHESES

Based on TAM and TOE, this study proposes a conceptual framework examining the relationship between Perceived Usefulness, Perceived Ease of Use, and Attitude Toward Usage (ATU), and their influence on students' behavioral intention to use AI tools. The hypotheses suggest that PU, PEOU, and ATU significantly affect students' learning outcomes and skill development, with AI adoption expected to enhance both measurable academic achievements and broader competencies as shown in Figure 1.



The use of AI tools has no significant impact on students' learning outcomes and skill development.

H1: Perceived usefulness of AI tools significantly influences students' learning outcomes and their intention to use AI tools in education.

H2: Perceived ease of use of AI tools significantly influences students' learning outcomes and their intention to use these tools.

H3: Attitude Toward Use of AI tools significantly influence their actual usage of these tools for learning.

This study involves students from multiple educational institutions, divided into an experimental group (using AI tools) and a control group (not using AI tools). The study measure students' perceptions of AI tools in terms of usefulness, ease of use, and attitudes. The independent variable is the usage of AI tools, while the dependent variables are students' learning outcomes (test scores) and skill development (assessed through skills tests and self-reported surveys).

METHODOLOGY

This study employs a quantitative research methodology to systematically investigate the impact of artificial intelligence (AI) tools on students' learning outcomes and skill development. The quantitative approach is chosen for its objectivity, precision, and statistical rigor, allowing the researcher to quantify the effects of AI integration in education and to produce findings that are both reliable and generalizable. This approach aligns with the study's goal of providing measurable, evidence-based insights into how AI tools enhance students' academic performance and cognitive skills. The study follows a descriptive and correlational quantitative design, enabling both the description of current trends in AI adoption and the exploration of relationships between AI usage and educational outcomes. Quantitative data were collected to provide concrete and measurable evidence of how AI tools influence students' academic performance, engagement, and skill acquisition. The research problem and objectives are clearly defined to focus on determining the extent to which AI-driven educational interventions contribute to improved learning outcomes.

Two main instruments were used for data collection: structured surveys and standardized tests. The structured survey gathered information on students' frequency of AI tool usage, attitudes toward these technologies, and perceived improvements in their learning experiences. The questionnaire incorporated a mix of Likert-scale and multiple-choice questions to ensure a comprehensive understanding of students' perceptions. Pre-testing of the survey instrument was conducted to enhance clarity, reliability, and validity, following established best practices (Dillman, Smyth, & Christian, 2014). The standardized tests provided objective measures of academic achievement and skill development. These assessments were selected based on their relevance to subjects that integrate AI tools, such as mathematics, science, and language learning. They were designed to capture improvements in competencies like problem-solving, critical thinking, and analytical reasoning—skills widely recognized as essential in AI-supported learning environments (Chen, L., Chen, P., & Lin, Z., 2020).

A stratified random sampling method was employed to ensure representation across different educational levels and disciplines in Melaka, Malaysia. This approach allowed the population to be divided into specific subgroups such as age, academic level, or subject area, ensuring that all groups were adequately represented in the final sample. The method enhances the precision and external validity of the results by reducing sampling bias and ensuring that findings reflect the diversity of the broader student population (Creswell & Creswell, 2017). The sample size was determined through power analysis to guarantee sufficient statistical power to detect significant relationships between variables (Cohen, 1988).

Collected data were analyzed using statistical software to ensure accuracy, consistency, and efficiency. The analysis began with data cleaning to remove inconsistencies, followed by descriptive statistics (mean, median, and standard deviation) to summarize the main features of the data. Inferential statistics, including t-tests, ANOVA, and regression analysis, were employed to test hypotheses and explore relationships between AI usage and learning outcomes. These techniques allowed for identifying significant patterns and correlations and determining the strength and direction of relationships among variables. Statistical analysis also enabled the assessment of validity and reliability. Internal validity was enhanced by controlling confounding variables such as prior exposure to AI tools, socioeconomic background, and baseline academic performance. External validity was strengthened through a diverse and representative sample, ensuring the generalizability of findings to similar educational contexts. Reliability was confirmed through pilot testing and the calculation of Cronbach's alpha, which evaluated internal consistency within the survey instrument. Additionally, test-retest reliability was employed to ensure the stability of responses over time (Creswell, 2014).

The research relied on primary data, collected directly from students across different educational institutions in Melaka. This ensured that the data were original, specific to the research objectives, and highly relevant to the study context. The survey instrument was carefully designed to align with the research objectives and included questions that captured both usage behavior and perceptions of AI tools. The combination of Likert-scale, multiple-choice, and open-ended questions allowed for a rich and comprehensive dataset. This design facilitated both quantitative measurement and qualitative interpretation of trends in AI tool adoption. The research was conducted in Melaka, chosen for its diverse educational landscape encompassing primary, secondary, and tertiary institutions. Melaka's growing emphasis on technological adoption in education made it a suitable context for exploring how AI tools influence teaching and learning processes. Data collection was carried out using a cross-sectional time horizon, capturing data at a specific point in time. This approach provided a snapshot of current practices and outcomes related to AI integration in education, aligning with the study's objective of assessing the immediate effects of AI usage among students (Saunders et al., 2016).

The study prioritized methodological rigor through multiple validation strategies. External validity was addressed by ensuring sample diversity and utilizing both online and offline data collection methods to reach students with different access levels to technology. Internal validity was enhanced by maintaining standardized procedures for administering surveys and tests and by controlling for extraneous variables. Reliability was strengthened through pre-testing, consistent measurement scales, and the use of established survey instruments. Ethical considerations were also incorporated into the research design. Participation was voluntary, and respondents were informed about the study's purpose, confidentiality measures, and data protection policies. Anonymity was maintained throughout data collection and analysis to ensure that participants' identities remained protected.

In summary, this study applies a rigorous, systematic, and data-driven quantitative methodology to examine how AI tools affect students' learning outcomes and skill development in Melaka. The research design combines structured surveys, standardized testing, and advanced statistical analysis to ensure reliable, valid, and generalizable results. Through its well-defined procedures, representative sampling, and emphasis on validity and reliability, this study provides empirical evidence that contributes to a deeper understanding of AI's transformative role in education. The methodology ensures that the findings are not only statistically robust but also meaningful for policymakers, educators, and researchers seeking to optimize AI integration in educational environments.

Analysis

Descriptive analyses were performed to summarize the demographic and construct-level characteristics of the 305 respondents. The gender distribution was balanced, with 48.2% male and 51.8% female participants. Most respondents (81%) were aged 22–24 years, representing senior undergraduate students, and 41.6% were in their fourth year of study. Students from six faculties participated, with the largest representation from the

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Faculty of Technology Management and Technopreneurship (FPTT, 23.9%) and the Faculty of Information and Communication Technology (FTMK, 21.0%). All respondents reported having used AI tools such as ChatGPT and Gemini in their studies, reflecting widespread adoption of AI-assisted learning among university students.

Table 1 presents the mean and standard deviation for each construct. All variables scored highly (means ≥ 4.84 on a 5-point Likert scale), demonstrating that respondents generally viewed AI tools as useful, easy to use, and beneficial to their academic performance. Behavioral Intention to Use (BI) recorded the highest mean (M = 4.95, SD = 0.25), followed by Attitude Toward Use (ATU, M = 4.94, SD = 0.27), Perceived Ease of Use (PEOU, M = 4.92, SD = 0.28), and Perceived Usefulness (PU, M = 4.85, SD = 0.37). These results suggest that students held a highly favorable perception of AI integration in their learning process.

Table 1. Descriptive Statistics of Study Variables

Variable	**Min**	**Max**	**Mean**	**SD**
Perceived Usefulness (PU)	3.00	5.00	4.85	0.37
Perceived Ease of Use (PEOU)	3.00	5.00	4.92	0.28
Attitude Toward Use (ATU)	3.00	5.00	4.94	0.27
Behavioral Intention to Use (BI)	2.60	5.00	4.95	0.25

(N = 305)

A Pearson correlation analysis was conducted to examine the linear relationships among all variables. As shown in Table 2, all correlations were positive and statistically significant at the 0.01 level (two-tailed). The relationship between Attitude Toward Use and Behavioral Intention to Use was the strongest ($r = 0.714$, $p < 0.001$), followed by Perceived Usefulness ($r = 0.512$, $p < 0.001$) and Perceived Ease of Use ($r = 0.404$, $p < 0.001$).

These results indicate that students with more positive attitudes toward AI, and those who perceive it as useful and easy to use, are more likely to intend continued use. The high correlation among the independent variables (e.g., PU–ATU = 0.696) suggests interrelated dimensions consistent with the Technology Acceptance Model (TAM).

Table 2. Pearson Correlations among Variables

Variable	**PU**	**PEOU**	**ATU**	**BI**
PU	1	.578**	.696**	.512**
PEOU	.578**	1	.582**	.404**
ATU	.696**	.582**	1	.714**
BI	.512**	.404**	.714**	1

Note: **p < 0.01 (two-tailed)**

(N = 305)

Reliability analysis using the full sample confirmed the consistency of all constructs. Cronbach's Alpha values ranged between 0.875 and 0.902 in Table 3, demonstrating excellent reliability. This confirms that the measurement scales consistently captured the underlying constructs across the larger dataset.

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Table 3. Reliability Analysis for Main Study

Construct	Cronbach's α	Items
Perceived Usefulness (PU)	0.878	5
Perceived Ease of Use (PEOU)	0.902	5
Attitude Toward Use (ATU)	0.875	5
Behavioral Intention to Use (BI)	0.896	5

(N = 305)

A multiple regression analysis was conducted to determine which independent variables significantly predicted students' behavioral intentions to use AI tools. The overall model in Table 4 was statistically significant, $F(3, 301) = 104.93$, $p < 0.001$, with a correlation coefficient $R = 0.715$ and $R^2 = 0.511$. This indicates that approximately 51.1% of the variance in Behavioral Intention to Use can be explained by the three predictors: Perceived Usefulness, Perceived Ease of Use, and Attitude Toward Use.

Table 4. Model Summary for Multiple Regression

	Value
R	0.715
R^2	0.511
Adjusted R^2	0.506
Std. Error of Estimate	0.1737

The ANOVA results in Table 5 confirm that the regression model is highly significant ($p < 0.001$), verifying the model's predictive validity.

Table 5. ANOVA Summary for Regression Model

Source	SS	df	MS	F	Sig.
Regression	9.497	3	3.166	104.929	.000
Residual	9.081	301	.030		
Total	18.579	304			

The coefficients in Table 6 show that only Attitude Toward Use (ATU) was a significant predictor of Behavioral Intention to Use (BI) ($\beta = 0.704$, $t = 11.94$, $p < 0.001$). Perceived Usefulness (PU) ($\beta = 0.038$, $p = 0.518$) and Perceived Ease of Use (PEOU) ($\beta = -0.028$, $p = 0.590$) were not statistically significant when controlling for attitude. This indicates that students' favorable attitudes toward AI tools play the dominant role in shaping their behavioral intentions.

Table 6. Regression Coefficients

Predictor	B	β	t	Sig.
(Constant)	1.740	—	8.501	.000

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Perceived Usefulness (PU)	0.025	0.038	0.647	.518
Perceived Ease of Use (PEOU)	−0.025	−0.028	−0.539	.590
Attitude Toward Use (ATU)	0.651	0.704	11.939	.000

These findings suggest that while usefulness and ease of use correlate positively with behavioral intention, their effects are largely indirect through attitude. The strength of ATU's coefficient implies that cultivating positive emotional and cognitive responses toward AI is critical for encouraging adoption. The findings provide robust empirical evidence that Attitude Toward Use is the most powerful determinant of students' behavioral intentions to adopt AI tools in their learning process. Although Perceived Usefulness and Ease of Use contribute to forming positive attitudes, their direct effects on intention are insignificant when attitude is included in the model. This pattern aligns with the core assumptions of the Technology Acceptance Model (TAM), which posits that attitude serves as a mediating factor linking beliefs (usefulness, ease of use) with behavioral intention.

The high mean values across constructs reflect students' strong acceptance of AI in education, and the high Cronbach's Alpha coefficients confirm the reliability of the measurement scales. The overall model explains more than half of the variance in behavioral intention ($R^2 = 0.511$), which is substantial for behavioral research in educational technology. These results underscore the importance of fostering positive student attitudes toward AI through practical training, awareness, and demonstrating value rather than focusing solely on technical ease or perceived utility.

H1: Perceived usefulness of AI tools not significant influences students' learning outcomes and their intention to use AI tools in education.

Although correlation analysis showed a moderate positive association between PU and BI ($r = 0.512$, $p < 0.01$), regression analysis revealed that PU does not significantly predict behavioral intention ($p = 0.518$). This indicates that while students generally perceive AI tools as useful, usefulness alone does not determine their intention to use them.

This finding aligns with Venkatesh and Bala (2008), who suggest that perceived usefulness often operates indirectly through attitude rather than as a direct predictor. In this context, the widespread use of AI tools among students may have normalized their perceived usefulness, reducing its influence on behavioral intention. Students may instead prioritize aspects such as trust, ethical use, or relevance to learning outcomes, which are not captured solely by perceived usefulness. Hence, while PU contributes to shaping favorable attitudes, it does not independently motivate AI adoption in this study.

H2: Perceived Ease of Use (PEOU) of AI tools not significant influences students' learning outcomes and their intention to use these tools.

The data revealed that PEOU had no significant direct influence on BI ($\beta = -0.028$, $p = 0.590$), even though a positive correlation existed ($r = 0.404$, $p < 0.01$). This suggests that ease of use, while important in early technology adoption stages, is no longer a critical determinant among students who are already accustomed to user-friendly AI interfaces.

According to Venkatesh and Davis (2000), once a technology becomes familiar, the ease-of-use factor diminishes in predictive power because users focus on higher-order outcomes such as efficiency, effectiveness, or ethical trustworthiness. The respondents, being digitally literate and experienced users, likely perceived most AI platforms as intuitive and easy to navigate, leaving little variance in this construct. Thus, PEOU indirectly influences adoption by reinforcing positive attitudes rather than directly shaping behavioral intention.

H3: Attitude Toward Use (ATU) positively influences Behavioral Intention to Use AI tools.

The regression analysis confirmed that Attitude Toward Use (ATU) is the strongest and only significant

predictor of behavioral intention ($\beta = 0.704$, $p < 0.001$). This indicates that students with more favorable attitudes toward AI tools are substantially more likely to continue using them for learning and problem-solving activities. This outcome supports the Technology Acceptance Model (TAM) and the Theory of Reasoned Action (Ajzen & Fishbein, 1980), which propose that attitude serves as a key mediator between beliefs (usefulness, ease of use) and behavioral intention. Similar findings by Williamson and Eynon (2023) and Seo et al. (2021) reinforce that positive attitudes formed through enjoyment, trust, and perceived value are decisive in shaping adoption behaviors. In the present study, students' attitudes reflect their motivation to integrate AI into their academic work, particularly because they associate AI tools with enhanced understanding, efficiency, and creativity.

CONCLUSION

The findings confirm that Attitude Toward Use is the principal determinant of AI tool adoption among university students, while Perceived Usefulness and Perceived Ease of Use have only indirect effects. The results suggest that the academic environment has matured to a stage where technical usability is no longer a barrier; rather, emotional engagement, trust, and perceived relevance now shape behavioral intention. From a practical standpoint, educational institutions should prioritize strategies that foster positive student attitudes toward AI tools such as workshops, real-world demonstrations, and ethical awareness programs. Emphasizing AI's academic value, transparency, and potential for creative learning will enhance students' confidence and motivation to use these tools responsibly.

In conclusion, while perceived usefulness and ease of use are foundational beliefs, they are insufficient on their own to drive continued adoption. Instead, students' positive attitudes rooted in trust, interest, and perceived educational benefit serve as the critical link between cognition and behavior. This insight is vital for universities and policymakers seeking to embed AI technologies effectively within higher education frameworks.

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