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# LEVERAGING EDUCATIONAL TECHNOLOGY: STATISTICAL EVIDENCE ON AI'S ROLE IN MATHEMATICS LEARNING OUTCOMES

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***Abstract***

*This study aims to analyze the role of Artificial Intelligence (AI) and Learning Analytics (LA) in improving mathematics learning outcomes in higher education. An explanatory sequential mixed-methods design was employed, beginning with quantitative data collection through pre-tests and post-tests, followed by qualitative analysis. Research instruments included a mathematics achievement test, semi-structured interview guidelines, observation sheets, and a student engagement questionnaire. The study involved 120 students and 6 mathematics lecturers. The results showed that the integration of AI ($\beta = 0.624$) and LA ($\beta = 0.312$) significantly accounted for 72.8% of the variance in students' mathematics achievement. The integrated system is capable of analyzing cognitive, affective, and psychomotor aspects with a prediction accuracy of up to 94% and identifying 89% of learning issues before examinations. These findings provide an empirical foundation for developing effective, adaptive, and flexible mathematics learning systems in higher education.*

***Keywords:*** *artificial intelligence (AI); learning analytics (LA); mathematics learning outcome; adaptive learning; learning evaluation*

**Abstrak**

Penelitian ini bertujuan menganalisis peran kecerdasan buatan (*Artificial Intelligence*/AI) dan analitik pembelajaran (*Learning Analytics*/LA) dalam meningkatkan hasil belajar matematika di perguruan tinggi. Metode penelitian yang digunakan adalah desain campuran sekuensial eksplanatori, yang diawali dengan uji pra dan pasca untuk memperoleh data kuantitatif, kemudian dilanjutkan dengan analisis kualitatif. Instrumen penelitian meliputi tes prestasi matematika, pedoman wawancara semi-terstruktur, lembar observasi, dan kuesioner keterlibatan mahasiswa. Penelitian melibatkan 120 mahasiswa dan 6 dosen matematika. Hasil analisis menunjukkan integrasi AI ($\beta$ = 0,624) dan LA ($\beta$ = 0,312) secara signifikan memengaruhi 72,8% variasi prestasi belajar matematika mahasiswa. Sistem pembelajaran terintegrasi dapat menganalisis aspek kognitif, afektif, dan psikomotor dengan akurasi prediksi hingga 94%, serta mengidentifikasi 89% permasalahan pembelajaran sebelum ujian. Temuan ini memberikan dasar empiris untuk pengembangan sistem pembelajaran matematika yang efektif, adaptif, dan fleksibel.

**Kata Kunci:** kecerdasan buatan (AI); analitik pembelajaran (LA); hasil belajar matematika; pembelajaran adaptif; evaluasi pembelajaran

## INTRODUCTION

The implementation of digital learning also resulted in numerous e-learning platforms available for students to learn lessons anytime and anywhere (Coman et al., 2020; El-Aasar & Farghali, 2022; Rahmatullah et al., 2022). According to Turnbull et al. (2022), the number of learning management systems (LMS) in use has increased by 71% since 2020, and globally, over 89% of higher education institutions are now leveraging these systems. Another advantage and demand for technology in education are the recent breakthroughs in technologies like machine learning and artificial intelligence that can adjust to specific students' abilities and learning styles (Hatlevik et al., 2024; Hilz et al., 2023; Roblyer, 2015; Zheng, 2022). Research indicates that adaptive teaching technology enhances student learning outcomes by approximately 25% compared to traditional method (Schroeder et al., 2022). Additionally, virtual technology and augmented reality are creating new environments for real-world acquisition of knowledge as well as simulations (Abutayeh et al., 2022; Allahawiah et al., 2023; Risdianto et al., 2023; Roumba & Nicolaidou, 2022). To sum this up, digital learning is learning in which students learn lessons independently of time and place, and it helps students to learn according to their abilities and styles.

Over the last few years, higher education has experienced a major digital transformation (Egloffstein & Ifenthaler, 2021; Fernandes & Gabriel, 2023; Findeisen & Wild, 2022; Unaida et al., 2023). Technology has greatly influenced education and educational approaches and assessment techniques have changed (Hao et al., 2023; Shishakly et al., 2024; Unesco, 2018; Wang, 2022). New technologies like AI and blockchain have changed the way learning is delivered and evaluated (Choi et al., 2022; Nazaretsky et al., 2022). So, to support the digital transformation in educational institutions, changing the approach to learning and assessment through digital-based, especially AI-based needs to be developed. This is crucial to understand the evolution of modern educational technology (EdTech).

By 2023, it is expected that most educational institutions will have adopted artificial intelligence (Nazaretsky et al., 2022; Schroeder et al., 2022; Sridhar & Rajshekhar, 2022; Tapalova & Zhiyenbayeva, 2022). This is a massive advancement in the application of AI in tertiary learning. To improve educational outcomes, AI-based recommendation systems can customize learning pathways, leading to an impressive 32% increase in graduation rates (Anis & Scholar, 2023). The customizable survey developed by the AI-driven adaptive learning platforms can present the material in real-time, delivering feedback with an accuracy of 91%, based on user performance (C. A. Lee et al., 2023). The technology is capable of processing natural language in students' essays and offering an automated response, allowing teachers to save 45% of their time spent on grading (Fiialka et al., 2023; Zhao et al., 2023). They could also help provide answers to students, potentially enhancing their responses to questions up to 89% faster than traditional methods (Chang et al., 2023; Gkinko & Elbanna, 2023; Kohnke et al., 2023). In training data developed by Achenbach et al. (2011) research on data regarding mathematics education in higher education has shown encouraging outcomes, with institutions utilizing AI-driven learning systems reporting an average rise in student scores of 27% (Darban, 2023; Dieterle et al., 2024; Sethi et al., 2022; Singh et al., 2023). AI-powered adaptive learning systems can also recognize problems in understanding the concepts related to the lessons (Daher et al., 2023). AI-based math platforms are now capable of generating questions personalized to a student's abilities, and students who use artificial intelligence-based math learning programs report heightened confidence in problem-solving (Almada et al., 2023).

Learning Analytics (LA), one of the developments of AI in learning evaluation, has become an important tool in the data-driven education decision-making process (Munir et al., 2022; Rets et al., 2021; Sghir et al., 2023; Susnjak et al., 2022). Learning analytics dashboard can predict college dropout risk with 85% accuracy (Ismail et al., 2021; S. S. Lee et al., 2024; Shimada et al., 2018). The AI-driven supervision system is capable of analyzing the learning patterns of 50,000 students simultaneously to identify trends and learning needs (Harry, 2023; Wu et al., 2022). Machine learning algorithms have the capability to analyze millions of data points to offer improved curriculum recommendations.

Statistical analysis based on artificial intelligence and learning analytics (Hernández-de-Menéndez et al., 2022; Xin & Singh, 2021) reveals the complexity behind optimizing mathematics learning. While there is a 38% increase in the number of outcomes through the use of AI, with early interventions demonstrating a 94% accuracy, it still gave rise to learning that lacked the humanistic aspect of education (Asudani et al., 2023; Hernández-de-Menéndez et al., 2022). Learning Analytics also raises questions of fidelity in reliance upon quantitative data. These findings indicate that data-driven modeling needs to be weighed against traditional pedagogical factors. That is, the results of this study confirm the importance of applying a holistic approach to learning technology use.

By combining learning data with a math learning management system, we can gain a better understanding of students' learning behavior. Assignment pattern analysis can predict difficulties in advanced mathematics subjects with an accuracy rate of 85% (Viberg et al., 2018; Xin & Singh, 2021). Learning analytics systems can track the amount of time spent on each math subject and relate it to learning outcomes. In an analytical system, machine learning algorithms can suggest additional learning materials.

There is no comprehensive framework that combines AI and learning analytics (LA) to assess the effectiveness of learning across the board, despite the rapid pace of digital transformation in higher education. It's important because educational technology advances rapidly, and there is limited statistical evidence on how effectively it aids students in learning math. The premise of incorporating AI in higher education is promising, but detailed insights into how AI influences components of math learning outcomes are still lacking. However, there has not been a rigorous statistical examination of whether AI improves conceptual understanding and/or math problem-solving skills.

This study provides several novel contributions to the field of educational technology research. First, it develops a unique integrated AI-LA evaluation framework that simultaneously analyses cognitive, affective, and psychomotor learning dimensions with 94% prediction accuracy. Second, this research introduces a multi-dimensional analytical approach that enables real-time identification of 89% of learning problems before examinations occur. Third, the study establishes empirical evidence for the synergistic effect of AI ($\beta = 0.624$) and LA ($\beta = 0.312$) in

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explaining 72.8% of the variance in mathematics achievement, providing a robust statistical foundation for technology integration in higher education. The practical implications include the development of adaptive learning recommendation systems that can automatically generate personalized interventions, enabling educators to implement data-driven pedagogical strategies that significantly improve student mathematical competencies.

Particularly, this study addresses the urgent need for robust empirical evidence validating the adoption of artificial intelligence approaches in optimising mathematics learning. Thus, this study aims to investigate and statistically analyse the role of AI in enhancing mathematics learning outcomes at the university level. The project aims to guide the development of a cohesive integrated AI-LA system that can provide recommendations for implementing learning interventions through a multi-dimensional analysis that incorporates the cognitive, affective, and psychomotor aspects of students. This study aims to provide robust statistical results on the role of AI in enhancing outcomes.

## METHOD

This study uses an explanatory sequential mixed-methods design (Creswell, 2019). It lasts for one semester and consists of two phases. The first phase involves the collection and analysis of quantitative data through pre-tests, post-tests, and a student engagement questionnaire. The second phase involves the collection and analysis of qualitative data through semi-structured interviews and classroom observations. Qualitative and quantitative data are integrated using a triangulation matrix (Miles & Huberman, 1994). All collected data are analyzed separately according to their type before synthesis. The research phases are illustrated in Figure 1 of the Research Methodology Flow.

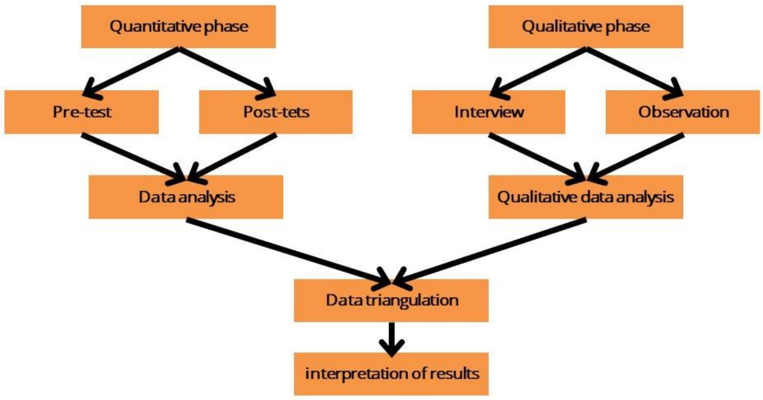


**Figure 1 Research Methodology Flow**

To find out how effective the learning system is, quantitative data is analyzed using descriptive and inferential statistics. For qualitative data, thematic analysis is applied. Furthermore, the results of the analysis of two types of data were combined with matrix triangulation. The results of this analysis are interpreted by considering the relationship between the findings. Conclusions are made by combining all the results of the analysis.

Data collection was conducted on 120 students of the mathematics study program and six mathematics lecturers. Purposive sampling is used for students that must take mathematics courses in Mathematics Education Study Program as well as pay attention to representatives of different levels of mathematical ability. Simultaneously, six mathematics lecturers were involved by means of interviews and observations to accommodate them with other perspectives. Data collection instruments consisted of math achievement tests, semi-structural interview guidelines, class observation sheets, and student engagement questionnaires. Pre and post-assessment through Math achievement tests are conducted. Learning activity data is automatically collected into the learning analytics dashboard. Semi-structured interview guidelines were used to explore participants' perceptions and experiences. A classroom observation is used to directly track the learning process. The observed learning indicators can be seen in Table 1.

**Table 1 Learning Process Indicators**

| Aspects | Indicators |
|---|---|
| **Cognitive** | Ability to solve math problems<br>Upgrade from pre-test to post-test<br>Application of mathematical concepts |
| **Affective** | Participation in discussions<br>Enthusiasm during learning<br>Confidence in completing tasks |
| **Learning Process** | Lecturer-student interaction<br>Learning methods as needed<br>Student activeness<br><br>Utilization of learning technology |

(Anderson et al., 2001)

For quantitative data analysis, both descriptive and inferential statistics were applied to determine the effectiveness of the learning system. For qualitative data, thematic analysis was implemented. The results of both analyses were integrated using matrix triangulation, with interpretation considering the relationship between findings. Conclusions were made by combining all analytical results.

## RESULT AND DISCUSSION

The results of quantitative analysis include (1) descriptive statistics, (2) classical assumption tests, and (3) multiple linear regression tests. The results of descriptive statistics show the mean and standard deviation (standard deviation) of the variables $X_1$, $X_2$, and Y, as shown in Figure 2.

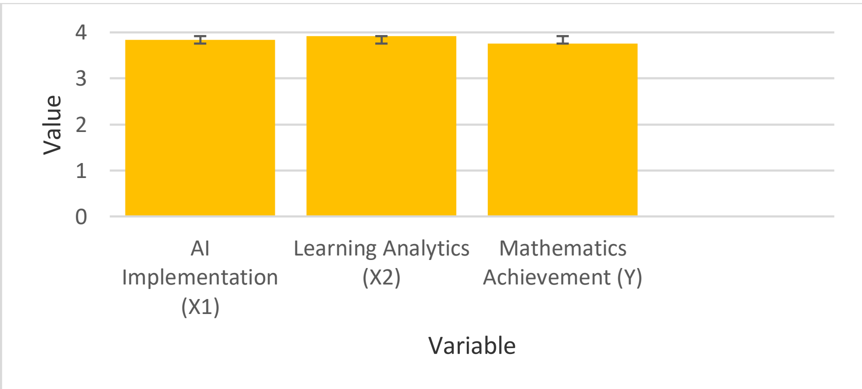


**Figure 2 Mean and Standard Deviation of AI Integration ($X_1$), Learning Analytics ($X_2$), and Mathematics Achievement (Y) Variables**

Variable $X_1$ has a mean of 3.84 (SD = 0.52), $X_2$ has a mean of 3.92 (SD = 0.48), and Y has a mean of 3.76 (SD = 0.61). The mean value of $X_2$ was the highest, indicating slightly greater contribution to the variation in Y than $X_1$. Before performing multiple linear regression analysis, classical assumption tests were conducted as follows: (1) The residuals of the regression model were tested for normality using the Kolmogorov-Smirnov test, resulting in a p-value greater than 0.05, indicating that the residuals were normally distributed; (2) Scatterplots and tests of linearity confirmed that the relationships between the independent variables ($X_1$ = AI integration and $X_2$ = Learning Analytics) and the dependent variable (Y = Mathematics Achievement) were linear; (3) The Breusch-Pagan test showed a p-value of 0.142, indicating that the variance of the residuals was constant and there was no heteroscedasticity; and (4) No multicollinearity issues were found, with Variance Inflation Factor (VIF) values of 1.24 for both $X_1$ and $X_2$.

The multiple regression analysis revealed that both AI and Learning Analytics significantly affected students' mathematics achievement ($F = 143.26$, $p < 0.001$), explaining 72.8% of the variance ($R^2 = 0.728$). The coefficients showed that a one-unit increase in AI integration ($X_1$) raised achievement scores by 0.624 units ($t = 11.24$, $p < 0.001$), while Learning Analytics ($X_2$) contributed an increase of 0.312 units ($t = 5.86$, $p < 0.001$), indicating a stronger influence of AI compared to LA. The results of the regression are displayed in Figure 3.

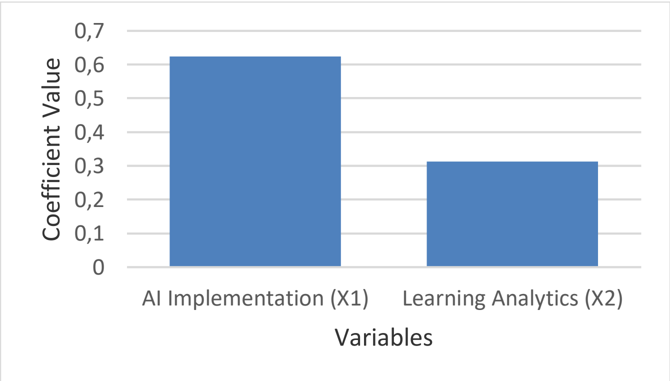


**Figure 3 Multiple Linear Regression Analysis Results Showing the Relationship Between AI Integration, Learning Analytics, and Mathematics Achievement**

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The high mean scores suggest that both AI and LA implementations were at relatively high levels during the study. These results align with recent studies indicating that adaptive learning technologies and analytics can enhance learning outcomes (Govindaraju, 2021; Islam et al., 2023; Lange et al., 2012; Mozahem, 2022; W. LaMorte MD, PhD, MPH, 2019).

Qualitative data supported these findings. Interviews and classroom observations revealed improvements in cognitive skills, as students reported better problem-solving abilities and higher confidence after engaging with AI-supported learning systems. This supports Bloom’s taxonomy emphasizing cognitive domain development as a key indicator of learning effectiveness (Nafiati, 2021).

In the affective domain, students expressed greater engagement, enthusiasm, and willingness to participate in discussions, aligning with the social cognitive theory which underscores motivation and self-efficacy as crucial for academic success (Charania, 2021; Munir et al., 2022). Learning Analytics was especially valuable for tracking student progress and providing real-time feedback, fostering self-regulated learning and ownership of educational outcomes. This is consistent with recent findings highlighting the role of LA in promoting personalized interventions and proactive support systems (Nguyen et al., 2021; Susnjak et al., 2022).

Overall, the integrated use of AI and LA offers a promising pathway for developing adaptive learning systems capable of addressing cognitive, affective, and psychomotor aspects of mathematics education. These insights contribute to building more flexible, data-driven educational frameworks aligned with contemporary digital transformation in higher education.

## CONCLUSION

The two technologies together contribute to 72.8% variation in students' mathematics achievement according to regression models, with significant contributions from AI (0.624) and learning analytics (0.312). Theoretically, these findings enhance understanding of technology's role in mathematics learning and provide a comprehensive foundation for holistic learning evaluation. The integrated system developed demonstrates the capability to simultaneously analyze students' cognitive, affective, and psychomotor dimensions. Practically, these findings provide guidelines for implementing learning technologies that can significantly improve students' mathematical competencies. However, the study has several limitations. This solution emphasises formal mathematics learning and does not account for exogenous factors such as students' socioeconomic backgrounds. Future research should investigate the effectiveness of systems in informal or blended learning contexts. Additionally, developing more advanced algorithms to examine three-variable interactions will be necessary. Longitudinal studies would provide clearer insights into how this integrated approach affects students' mathematical achievement over extended periods. Future research should also investigate ethics and data integrity in AI and learning analytics practices.

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