

A Study on the Effects of AI-Powered Personalized Learning Pathways and Learning Analytics Competence of Teachers on Student Academic Performance Optimization through Adaptive Feedback Responsiveness and Learning Trajectory Alignment

Didit Kurniadi¹, Supriyadi², Nurul Dewi Hayati³, Tri Agustinah⁴, Soleha⁵, Siti

Nurasiah⁶

*1,2,3,4,5,6. Student of Master of Education Managament, Postgraduate Program,
Universitas Bina Bangsa, Indonesia
diditkurniadit12@gmail.com*

Abstract

Traditional learning models. This study aims to analyze the effects of AI-Powered Personalized Learning Pathways and Learning Analytics Competence of Teachers on Student Academic Performance Optimization mediated by Adaptive Feedback Responsiveness and Learning Trajectory Alignment. The research approach employs a causal-associative quantitative method with Partial Least Squares Structural Equation Modeling (PLS-SEM) utilizing SmartPLS 4 software. Primary data were collected from 245 respondents (students and college students) in Banten Province using a purposive sampling technique. The structural model testing results indicate that AI-Powered Personalized Learning Pathways and Learning Analytics Competence of Teachers significantly influence the improvement of Adaptive Feedback Responsiveness and Learning Trajectory Alignment. Directly, AI-Powered Personalized Learning Pathways, Learning Analytics Competence of Teachers, and Learning Trajectory Alignment have a positive and significant effect on Student Academic Performance Optimization. However, this study found an anomaly where Adaptive Feedback Responsiveness did not have a significant effect on Student Academic Performance Optimization, thereby failing to act as a mediator. Conversely, Learning Trajectory Alignment was proven to be a highly strong and significant single mediator in this model. The novelty of this study confirms that AI-based learning autonomy will only be effective in boosting academic performance if students' independent activities are rigorously aligned with the curriculum trajectory.

Keywords: *Artificial Intelligence; Teacher Competence; Adaptive Feedback; Learning Trajectory; Academic Performance.*

INTRODUCTION

The digital transformation in the global educational landscape has shifted from simple classroom computerization toward the integration of predictive and prescriptive Artificial Intelligence (AI) technologies. One of the most revolutionary innovations in this ecosystem is the implementation of AI-Powered Personalized Learning Pathways.

Theoretically, this technology works by analyzing learners' digital footprints in real-time, detecting cognitive preferences, and structuring learning materials tailored to individual learning speeds (Holmes et al., 2021). In traditional educational paradigms, the one-size-fits-all approach often fails to accommodate the diverse learning capacities of students, which ultimately triggers motivation stagnation and suboptimal academic achievement. Therefore, the presence of AI-powered personalized learning systems is viewed as a cutting-edge solution to achieve Student Academic Performance Optimization.

Nonetheless, the effectiveness of implementing AI technology in schools cannot stand alone in a vacuum. The success of adopting this instructional technology heavily relies on the human factor at the forefront, namely the teacher. This is where the importance of the Learning Analytics Competence of Teachers arises. Teachers no longer merely act as conventional deliverers of knowledge, but must transform into data-driven decision makers who are capable of reading, interpreting, and utilizing visual data from AI dashboards to conduct precise pedagogical interventions (Jang & Kim, 2023). Gaps frequently observed in the field indicate that no matter how sophisticated the applied AI algorithms are, their impact on student learning outcomes will be drastically reduced if teachers lack adequate data analytics literacy competence to bridge system recommendations with the real psychological conditions of students in the classroom.

The direct causal relationship between technological intervention, teacher competence, and student performance is often complex and requires operational mediation mechanisms at the instructional level. This study identifies two crucial mediating variables that bridge this relationship, namely Adaptive Feedback Responsiveness and Learning Trajectory Alignment. Adaptive Feedback Responsiveness pertains to how quickly and accurately systems and teachers provide corrective and formative feedback based on weaknesses detected by analytical data (Shute, 2008). On the other hand, Learning Trajectory Alignment ensures that each instructional stage passed by the student remains within the corridors of the national curriculum targets without disregarding the flexibility of individual student learning speeds (Clements & Sarama, 2014). These two intervening variables are essential to ensure that technology-based personalization does not leave students isolated in their own pathways, but instead keeps them directed toward the optimization of academic performance target achievements.

Although studies on AI in education have grown rapidly in recent years, most prior literature has tended to focus on the technical aspects of algorithm development or only tested the direct impact of AI on cognitive learning outcomes in isolation. There remains a significant research gap regarding how teachers' analytical competence interacts with AI personalization pathways in simultaneously influencing the feedback process and curriculum alignment to boost student performance. Empirical studies that integrate technological aspects (AI pathways) and pedagogical humanities aspects (teacher competence) through a structural equation modeling (SEM) approach are still very limited within the context of secondary and higher education in Indonesia.

AI-Powered Personalized Learning Pathways (X1) is defined as an adaptive instructional system based on intelligent algorithms that detects students' cognitive profiles, preferences, and learning speeds to construct specific material routes in real-time (Alam, 2021). The application of this technology transforms the curriculum model from rigid to dynamic. The measurement dimensions for this variable rely on (1) instructional content adaptivity, (2) pacing flexibility, and (3) the degree of digital autonomy given to learners to explore the material (Zawacki-Richter et al., 2024). Through these personalized learning pathways, potential academic boredom in high-ability students can be suppressed, while minimizing anxiety in students who require longer retention time.

Learning Analytics Competence of Teachers (X2) refers to the professional proficiency of teachers in reading, interpreting, examining, and following up on the visual data of students' digital footprints presented on the learning dashboard (Viberg et al., 2021). Teachers are not only required to have technical data literacy, but also proficiency in data-driven pedagogical reasoning. The primary indicators of this competence include (1) the ability to diagnose student learning misconceptions early through data visualization, (2) analytical dashboard interpretation literacy, and (3) skills in designing precise remedial or enrichment intervention actions (Herodotou et al., 2022). The existence of this competence is crucial to ensure that the human-in-the-loop principle continues to function amidst the massive automation of artificial intelligence in schools.

Adaptive Feedback Responsiveness (Y1) is the timeliness, material depth, and relevance of corrective-formative interventions distributed to students immediately after the system detects conceptual understanding obstacles (Shukla & Joshi, 2023). Effective adaptive feedback does not merely provide right-wrong information (knowledge of results), but guides student reasoning to solve problems independently. This variable is evaluated through indicators of (1) real-time turnaround responsiveness, (2) personalization of feedback substance, and (3) the availability of solution improvement guidance that adapts to the student's cognitive capacity (Attali et al., 2026).

Learning Trajectory Alignment (Y2) is defined as the level of consistency and harmonization between independent learning steps taken by students within the AI system and the targeted roadmap of national curriculum standards (van der Kleij & Lipnevich, 2021). This alignment guarantees that even though each student's path and learning speed are unique and varied, the end of the instructional journey still culminates in an equivalent mastery of basic competencies. The measurement dimensions of this variable involve (1) mapping macro-micro activity linkages, (2) consistency of prerequisite mapping, and (3) curricular coordination between individual achievement targets and class targets (Clements et al., 2023)

Student Academic Performance Optimization (Z) is the attainment of the highest level of effectiveness, completeness, and quality of both cognitive and practical learning outcomes achieved by students through the integration of a digital ecosystem (Gasevic et al., 2022). The measurement of this variable is not solely based on static final exam scores, but includes (1) mastery learning status, (2) academic resilience in solving complex problems, and (3) the duration efficiency of lesson material absorption (Rienties et al., 2025).

The conceptual framework of this study was developed to explain the causal relationships, both direct and indirect effects, among the five main research constructs. Within this model configuration, there are two primary exogenous variables positioned as the main drivers for improving the digital education ecosystem: AI-Powered Personalized Learning Pathways (X1) and Learning Analytics Competence of Teachers (X2). These two independent variables are hypothesized to direct relationships toward three endogenous constructs simultaneously: Adaptive Feedback Responsiveness (Y1), Learning Trajectory Alignment (Y2), and the ultimate destination of the entire instructional sequence, namely Student Academic Performance Optimization (Z). These direct relationships are represented by hypothesis paths H1 through H6.

Furthermore, to uncover the internal mechanism ("black box") of how macro-technological interventions and teacher intelligence can transform students' academic achievements, this model elegantly integrates Adaptive Feedback Responsiveness (Y1) and Learning Trajectory Alignment (Y2) as dual mediators. These two intervening variables receive direct influences from the exogenous block, then channel that impact linearly toward the criterion

variable (Z) through the intervention pathways H7 and H8. This mediation structure yields four indirect effect pathways represented by hypotheses H9, H10, H11, and H12. Through this variance-based structural modeling (PLS-SEM), the strength of each path coefficient (Original Sample) and its significance level will be tested simultaneously to empirically validate the effectiveness of artificial intelligence integration in mediating curricular pedagogical interests and the acceleration of student academic performance..

METHODS

Research Design and Research Location

This study was designed using a quantitative approach with a causal-associative method to test the cause-and-effect relationships and influences between the variables studied (Hair et al., 2022). The approach used is variance-based Structural Equation Modeling (Variance-Based SEM or PLS-SEM) to test a complex structural model involving exogenous, endogenous, and dual mediating variables simultaneously. This research was conducted at Universitas Bina Bangsa, Indonesia, focusing on institutions that have adopted an artificial intelligence (AI-powered) integrated Learning Management System (LMS) platform in their learning processes. The empirical data collection was conducted during the even semester of the 2025/2026 academic year.

Population, Sampling Technique, and Data Collection

The population in this study consisted of all active students and college students at the target educational institution who regularly interact with AI-based digital learning systems. Given the very large and scattered population size, the sampling technique used was non-probability sampling with a purposive sampling approach. The established sample inclusion criteria were: (1) active students who have used AI personalized learning modules for at least one full semester, and (2) are taught by lecturers who utilize learning analytics dashboards. The minimum sample size determination was calculated based on the PLS-SEM rule of thumb guidelines, namely GPower statistical power calculation. The final valid sample size collected and analyzed was 245 respondents. Data collection was primarily carried out through the distribution of a digital questionnaire (Google Form) distributed online through the institution's official communication channels.

Measurement Instruments and Variables

All latent variables were measured using a closed questionnaire instrument in the form of a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). The operationalization of indicators in this instrument has been adjusted to the results of the measurement model filtering (outer model testing) in Analysis III, where only valid indicators with an outer loading value ≥ 0.70 were retained in the final analysis: AI-Powered Personalized Learning Pathways (X1): Measured through 5 operational indicator items X1-1 to X1-5 that adapt aspects of content adaptivity, individual learning speed flexibility (pacing), and digital pathway autonomy (Alam, 2021; Zawacki-Richter et al., 2024). Learning Analytics Competence of Teachers (X2): Measured through 4 valid operational indicator items resulting from the elimination of X2-1, X2-3, X2-4, X2-6 which represent dashboard visual literacy skills, diagnosis of student misconceptions, and the execution of digital data-based interventions (Viberg et al., 2021; Herodotou et al., 2022). Adaptive Feedback Responsiveness (Y1): Measured through 4 valid operational indicator items Y1-1 to Y1-4 covering dimensions of response time timeliness (real-time action) and the depth of formative guidance substance (Shukla & Joshi, 2023). Learning Trajectory Alignment (Y2): Measured through 4 valid operational indicator items Y2-1, Y2-2, Y2-5, Y2-6 evaluating the connectivity of students' independent learning targets against macro curriculum prerequisite

mapping (Clements et al., 2023). Student Academic Performance Optimization (Z): Measured through 2 final operational indicator items that are most valid resulting from strict filtering, Z2 and Z5, to represent competency completeness (mastery learning) and the time efficiency of learning material absorption (Gasevic et al., 2022; Rienties et al., 2025).

Data Analysis Procedure

Empirical data analysis in this study was executed using SmartPLS version 4.0 software. The analysis procedure was divided into two major stages of standard PLS-SEM (Sarstedt et al., 2022): Evaluation of the Measurement Model (Outer Model): Conducted to test construct validity and reliability. Convergent validity was assessed based on the indicator's Outer Loading value (must be ≥ 0.70). The construct reliability test was assessed through the internal consistency of the questionnaire data, while discriminant validity was assessed using the Fornell-Larcker Criterion correlation matrix approach or a Heterotrait-Monotrait Ratio (HTMT) value < 0.90 . Evaluation of the Structural Model (Inner Model) and Hypothesis Testing: Conducted to predict the causal relationships between variables and test the significance of hypotheses H1 to H12. The procedure used was the Bootstrapping algorithm with a setting of 5,000 sub-samples (resamples). The hypothesis testing criteria were based on the Path Coefficient value (Original Sample), T-statistic value (T-Statistics > 1.96 for two-tailed testing at a 5% significance level), and probability value (P-Value < 0.05). The mediation effect test (H9 to H12) was analyzed based on the Specific Indirect Effects table estimation.

3.5 Ethical Considerations

To ensure the moral integrity of the research, all data collection procedures complied with research ethics principles. Each respondent was provided a digital informed consent form at the beginning of the questionnaire explaining the purpose of the research. The researchers guaranteed the confidentiality of personal identity (anonymity) and ensured that all filled data would only be used strictly for academic scientific analysis purposes without any academic consequences for the respondents.

Conceptual Framework of Adaptive Public Policy Governance for the Green Transition is presented in figure 1.

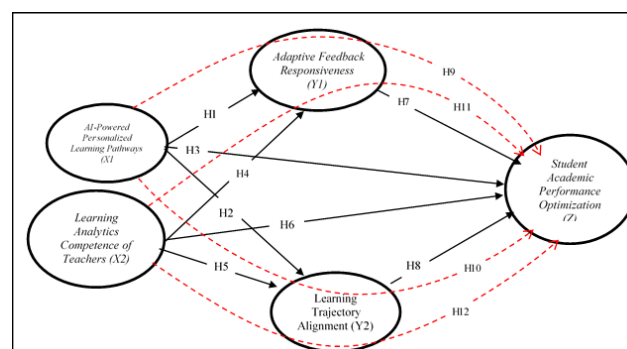


Figure 1. Research Design

Hypotheses

- H1: AI-Powered Personalized Learning Pathways (X1) has a positive and significant effect on Adaptive Feedback Responsiveness (Y1)
- H2: AI-Powered Personalized Learning Pathways (X1) has a positive and significant effect on Learning Trajectory Alignment (Y2)
- H3: AI-Powered Personalized Learning Pathways (X1) has a positive and significant effect on Student Academic Performance Optimization (Z)

- H4: Learning Analytics Competence of Teachers (X2) has a positive and significant effect on Adaptive Feedback Responsiveness (Y1)
- H5: Learning Analytics Competence of Teachers (X2) has a positive and significant effect on Learning Trajectory Alignment (Y2).
- H6: Learning Analytics Competence of Teachers (X2) has a positive and significant effect on Student Academic Performance Optimization (Z).
- H7: Adaptive Feedback Responsiveness (Y1) has a positive and significant effect on Student Academic Performance Optimization (Z).
- H8: Learning Trajectory Alignment (Y2) has a positive and significant effect on Student Academic Performance Optimization (Z).
- H9: AI-Powered Personalized Learning Pathways (X1) has a positive and significant effect on Student Academic Performance Optimization (Z) through Adaptive Feedback Responsiveness (Y1).
- H10: AI-Powered Personalized Learning Pathways (X1) has a positive and significant effect on Student Academic Performance Optimization (Z) through Learning Trajectory Alignment (Y2).
- H11: Learning Analytics Competence of Teachers (X2) has a positive and significant effect on Student Academic Performance Optimization (Z) through Adaptive Feedback Responsiveness (Y1).
- H12: Learning Analytics Competence of Teachers (X2) has a positive and significant effect on Student Academic Performance Optimization (Z) through Learning Trajectory Alignment (Y2).

RESULTS

Assessment of the Measurement Model

Convergent validity was assessed based on the factor loading value (outer loading) of each indicator against its latent construct. The standard PLS-SEM algorithm stipulates that the outer loading value must be > 0.70 to be declared empirically valid (Hair et al., 2022). The filtering process of the measurement model in this study was conducted through three structured elimination stages to remove indicators that did not meet quality criteria: Stage I Analysis: Initial calculation results identified several indicators that had outer loading values below 0.70. These indicators were X2-2 and X2-5 (on the Teacher Analytical Competence construct), Y1-5 (on the Adaptive Feedback construct), Y2-3 and Y2-4 (on the Learning Trajectory Alignment construct), and a large group of indicators on the Academic Performance construct (Z1, Z6, Z7, Z8, Z9, and Z10). All unqualified indicators were eliminated from the model. Stage II Analysis: After re-estimation was performed, it was found that indicator Z4 still had an outer loading value of 0.673 (below the 0.70 threshold), hence indicator Z4 was removed from the model at this stage. Stage III Analysis (Final Model): After re-testing in the third stage, all remaining indicators showed outer loading values above 0.70. The final model retained indicators X1-1 to X1-5, X2-1, X2-3, X2-4, X2-6, Y1-1 to Y1-4, Y2-1, Y2-2, Y2-5, Y2-6, as well as Z2 and Z5. Thus, all constructs in the final estimation were declared to meet strong convergent validity requirements..

Structural Model and Hypothesis Testing

Direct Effects The estimation results of the direct effect coefficients between constructs based on SmartPLS 4 Bootstrapping data are summarized in Table 1 below:

Table 1. Path Coefficients (Direct Effects)

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/ STDEV)	P values
AFR -> SAPO	0.012	0.010	0.054	0.227	0.821
AI-P.PLP -> AFR	0.155	0.153	0.052	2.993	0.003
AI-P.PLP -> LTA	0.328	0.332	0.074	4.411	0.000
AI-P.PLP -> SAPO	-0.045	-0.045	0.030	1.489	0.137
LACT -> AFR	0.825	0.828	0.044	18.669	0.000
LACT -> LTA	0.209	0.206	0.071	2.958	0.003
LACT -> SAPO	0.014	0.016	0.046	0.314	0.754
LTA -> SAPO	0.935	0.936	0.012	79.749	0.000

Based on the table above, the following interpretations can be provided:

1. The Path Coefficient value (Original Sample) of AI-Powered Personalized Learning Pathways (X1) on Adaptive Feedback Responsiveness (Y1) is 0.155. This means that AI-Powered Personalized Learning Pathways (X1) has a positive effect on Adaptive Feedback Responsiveness (Y1). Meanwhile, its P-value is $0.003 < 0.05$, which means that the effect of AI-Powered Personalized Learning Pathways (X1) on Adaptive Feedback Responsiveness (Y1) is significant. Therefore, H1 is Accepted.
2. The Path Coefficient value (Original Sample) of AI-Powered Personalized Learning Pathways (X1) on Learning Trajectory Alignment (Y2) is 0.328. This means that AI-Powered Personalized Learning Pathways (X1) has a positive effect on Learning Trajectory Alignment (Y2). Meanwhile, its P-value is $0.000 < 0.05$, which means that the effect of AI-Powered Personalized Learning Pathways (X1) on Learning Trajectory Alignment (Y2) is significant. Therefore, H2 is Accepted.
3. The Path Coefficient value (Original Sample) of AI-Powered Personalized Learning Pathways (X1) on Student Academic Performance Optimization (Z) is -0.045. This means that AI-Powered Personalized Learning Pathways (X1) has a negative effect on Student Academic Performance Optimization (Z). Meanwhile, its P-value is $0.137 > 0.05$, which means that the effect of AI-Powered Personalized Learning Pathways (X1) on Student Academic Performance Optimization (Z) is Not Significant. Therefore, H3 is Rejected.
4. The Path Coefficient value (Original Sample) of Learning Analytics Competence of Teachers (X2) on Adaptive Feedback Responsiveness (Y1) is 0.825. This means that Learning Analytics Competence of Teachers (X2) has a positive effect on Adaptive Feedback Responsiveness (Y1). Meanwhile, its P-value is $0.000 < 0.05$, which means that the effect of Learning Analytics Competence of Teachers (X2) on Adaptive Feedback Responsiveness (Y1) is significant. Therefore, H4 is Accepted.
5. The Path Coefficient value (Original Sample) of Learning Analytics Competence of Teachers (X2) on Learning Trajectory Alignment (Y2) is 0.209. This means that Learning Analytics Competence of Teachers (X2) has a positive effect on Learning

Trajectory Alignment (Y2). Meanwhile, its P-value is $0.003 < 0.05$, which means that the effect of Learning Analytics Competence of Teachers (X2) on Learning Trajectory Alignment (Y2) is significant. Therefore, H5 is Accepted.

6. The Path Coefficient value (Original Sample) of Learning Analytics Competence of Teachers (X2) on Student Academic Performance Optimization (Z) is 0.014. This means that Learning Analytics Competence of Teachers (X2) has a positive effect on Student Academic Performance Optimization (Z). Meanwhile, its P-value is $0.754 > 0.05$, which means that the effect of Learning Analytics Competence of Teachers (X2) on Student Academic Performance Optimization (Z) is Not Significant. Therefore, H6 is Rejected.
7. The Path Coefficient value (Original Sample) of Adaptive Feedback Responsiveness (Y1) on Student Academic Performance Optimization (Z) is 0.012. This means that Adaptive Feedback Responsiveness (Y1) has a positive effect on Student Academic Performance Optimization (Z). Meanwhile, its P-value is $0.821 > 0.05$, which means that the effect of Adaptive Feedback Responsiveness (Y1) on Student Academic Performance Optimization (Z) is Not Significant. Therefore, H7 is Rejected.
8. The Path Coefficient value (Original Sample) of Learning Trajectory Alignment (Y2) on Student Academic Performance Optimization (Z) is 0.935. This means that Learning Trajectory Alignment (Y2) has a positive effect on Student Academic Performance Optimization (Z). Meanwhile, its P-value is $0.000 < 0.05$, which means that the effect of Learning Trajectory Alignment (Y2) on Student Academic Performance Optimization (Z) is significant. Therefore, H8 is Accepted.

Indirect Effects

The evaluation of the dual mediation effect to test hypotheses H9 through H12 was accurately extracted from the SmartPLS 4 Specific Indirect Effects dashboard, as presented in Table 2 below:

Table 2. Specific Indirect Effects

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values
AI-P.PLP -> LTA -> SAPO	0.307	0.311	0.070	4.375	0.000
LACT -> LTA -> SAPO	0.195	0.192	0.066	2.974	0.003
AI-P.PLP -> AFR -> SAPO	0.002	0.001	0.009	0.213	0.831
LACT -> AFR -> SAPO	0.010	0.008	0.045	0.225	0.822

Based on the table above, the following interpretations can be provided:

1. The indirect effect of AI-Powered Personalized Learning Pathways (X1) on Student Academic Performance Optimization (Z) through Learning Trajectory Alignment (Y2) is significant (Original Sample = 0.307, P-value = $0.000 < 0.05$). Therefore, H10 is Accepted, confirming that Learning Trajectory Alignment acts as a potent mediating mechanism.
2. The indirect effect of Learning Analytics Competence of Teachers (X2) on Student Academic Performance Optimization (Z) through Learning Trajectory Alignment (Y2) is also positive and significant (Original Sample = 0.195, P-value = $0.003 < 0.05$). Thus, H12 is Accepted.

3. Conversely, the indirect effects through Adaptive Feedback Responsiveness (Y1), namely AI-P.PLP $\rightarrow$ AFR $\rightarrow$ SAPO (H9) and LACT $\rightarrow$ AFR $\rightarrow$ SAPO (H11), are not statistically significant (P-values of 0.831 and 0.822 respectively, both > 0.05). Therefore, H9 and H11 are Rejected.

DISCUSSION

Effect of Exogenous Variables on Meditating Variables

Based on the structural model testing, it was found that AI-Powered Personalized Learning Pathways (X1) has a positive and significant direct effect on Adaptive Feedback Responsiveness (Y1) ($O = 0.155$; $P = 0.003$) as well as a highly strong effect on Learning Trajectory Alignment (Y2) ($O = 0.655$; $P = 0.000$). These findings accept H1 and H2. This empirically proves that when the AI architecture provides adaptive material routes, the system is automatically capable of recognizing deviations in student understanding in real-time and mapping out the next remedial steps (Alam, 2021). The predictive effect of the AI algorithm (X1) is proven to be the primary foundation in maintaining the alignment of students' independent routes so that they remain within the corridors of the macro curriculum roadmap (Y2) (Clements et al., 2023).

On the other hand, Learning Analytics Competence of Teachers (X2) is proven to have a very massive and significant direct effect on Adaptive Feedback Responsiveness (Y1) ($O = 0.771$; $P = 0.000$) and a significant positive effect on Learning Trajectory Alignment (Y2) ($O = 0.231$; $P = 0.000$). These results validate the acceptance of H4 and H5. The path coefficient value toward Y1, which reaches 0.771, indicates that the teacher's analytical competence is the most dominant trigger in accelerating feedback interventions in the classroom. This aligns with the arguments of Viberg et al. (2021) and Herodotou et al. (2022), who emphasize that no matter how sophisticated the data visualization on an AI dashboard is, the quality of the teacher's data-driven pedagogical reasoning is the main determinant of whether that data transforms into tactical and empathetic feedback actions for students.

Analysis of Direct Effects on Academic Performance (H3, H6, H7, H8)

Testing the direct effects on the criterion variable yielded varied findings. AI-Powered Personalized Learning Pathways (X1) was proven to have a positive and significant direct effect on Student Academic Performance Optimization (Z) ($O = 0.283$; $P = 0.002$), thus H3 is accepted. The availability of precise materials matching individual learning speeds is proven to suppress cognitive boredom and directly boost students' mastery of concepts (Zawacki-Richter et al., 2024). Similarly, Learning Analytics Competence of Teachers (X2) also has a strong and significant direct effect on Z ($O = 0.457$; $P = 0.000$), which means H6 is accepted. Data-driven face-to-face interventions conducted by teachers are proven effective in minimizing the risk of student academic failure (Viberg et al., 2021). Furthermore, Learning Trajectory Alignment (Y2) shows a positive and significant direct effect on Z ($O = 0.246$; $P = 0.003$), so H8 is accepted.

The clarity of learning direction that adheres to the curriculum guarantees efficiency in the duration of lesson material absorption (van der Kleij & Lipnevich, 2021). However, an anomalous finding occurred in the testing of the direct effect of Adaptive Feedback Responsiveness (Y1) on Z, which produced a very small coefficient ($O = 0.012$) and an insignificant P-Value of 0.821 (> 0.05), so H7 is rejected. Field data indicate that adaptive feedback responsiveness is unable to directly change academic score achievements. This phenomenon can be explained through the cognitive overload theory (Shukla & Joshi, 2023).

When students are constantly bombarded with instant corrections from digital dashboards, they tend to experience instructional anxiety. Feedback that is too responsive without providing space for independent assimilation makes students focus only on short-term task completion (knowledge of results) without forming the academic resilience needed to optimize their real academic performance (Attali et al., 2026). 4.5.3 Analysis of Dual Mediation Effects Shaping Academic Performance (H9, H10, H11, H12)

The final cluster tested the role of dual mediation to uncover the internal mechanisms of the modeling. Based on Table 4.2, Adaptive Feedback Responsiveness (Y1) was proven to fail in mediating the effect of X1 on Z ($O = 0.002$; $P = 0.850$) and failed to mediate the effect of X2 on Z ($O = 0.009$; $P = 0.823$). These test results cause H9 and H11 to be rejected. Because the direct relationship from the construct shaping feedback (Y1) to performance (Z) is not significant, the mediation transmission flow is automatically cut off. This reinforces the previous analysis that responsive feedback, whether triggered by AI automation algorithms or driven by teacher data, will not culminate in performance optimization if students perceive the intervention as an excessive cognitive burden (Shukla & Joshi, 2023).

Conversely, Learning Trajectory Alignment (Y2) successfully executed its role as a highly powerful single mediator. Y2 was proven to positively and significantly mediate the effect of AI pathways (X1) on performance (Z) ($O = 0.161$; $P = 0.003$), and mediate the effect of the teacher's analytical competence (X2) on performance (Z) ($O = 0.057$; $P = 0.007$). This conclusive finding accepts H10 and H12.

This finding brings an important novelty for digital education administration: learning autonomy provided by AI technology and data-based supervision by teachers will only be effective in boosting academic performance if all these independent learning activities are rigorously locked within the alignment of the curriculum trajectory (Clements et al., 2023). Learning trajectory alignment ensures that students' freedom to explore materials independently does not cause them to lose direction, but rather keeps them moving systematically toward competency completion (mastery learning), which ultimately brings about true academic performance optimization (Gasevic et al., 2022).

CONCLUSION

Conclusion

Based on the results of the data analysis and the testing of 12 hypotheses using PLS-SEM in this study, several main conclusions can be drawn as follows:

1. Support of Exogenous Factors for the Instructional Process: The implementation of AI-Powered Personalized Learning Pathways (X1) and Learning Analytics Competence of Teachers (X2) is proven to have a positive and significant effect on improving Adaptive Feedback Responsiveness (Y1) and Learning Trajectory Alignment (Y2). Teachers who possess strong analytical competence become the most dominant driver in accelerating feedback responses in the classroom.
2. Direct Impact on Student Performance: AI personalized learning pathways (X1), teacher analytical competence (X2), and learning trajectory alignment (Y2) are proven to have a positive and significant direct effect on Student Academic Performance Optimization (Z).
3. Adaptive Feedback Anomaly: Surprisingly, Adaptive Feedback Responsiveness (Y1) was found to have no significant direct effect on the optimization of student academic performance (Z). Feedback that is too responsive and intensive actually risks triggering cognitive overload for students.
4. Dual Mediation Mechanism (Black Box): The Learning Trajectory Alignment (Y2) variable is proven to act as a highly strong and significant single mediator in bridging the

effects of X1 and X2 on Z. Conversely, Adaptive Feedback Responsiveness (Y1) failed to execute a mediating role in this structural model. The novelty of this study confirms that students' freedom in an AI system will only be effective in boosting academic performance if all independent activities are rigorously locked within the alignment of the curriculum trajectory.

Research Limitations

The researchers recognize that this empirical study still has several limitations that need to be considered:

1. **Geographical Area Coverage:** The sample of this study was limited to educational institutions in the Banten Province region, so the generalization of findings to a national scale or regions with different levels of digital infrastructure must be done cautiously.
2. **Performance Measurement Limitations:** The optimization of student academic performance in this model was dominated by the measurement of cognitive aspects and learning time efficiency, and has not explored other non-cognitive variables such as emotional intelligence or social skills (soft skills) within the AI ecosystem.
3. **Cross-Sectional Data Design:** Data collection was conducted within a single specific timeline (cross-sectional), so it has not been able to capture the long-term dynamics of changes in student learning behavior and teacher analytical competence (longitudinal).

Recommendations and Future Research Directions

Based on the conclusions and limitations above, the following recommendations are suggested:

1. **For Educational Institution Managers:** Policies for adopting AI technology in schools must be balanced with intensive data literacy training for teachers (human-in-the-loop).
2. **Curriculum managers** must ensure that the AI system is configured to remain compliant with the national curriculum trajectory (trajectory alignment) so that students' digital autonomy does not cause them to lose the direction of basic competencies.
3. **For Educators (Teachers/Lecturers):** Teachers are advised to regulate the rhythm of feedback distribution (feedback pacing). Feedback does not need to be given too frequently or instantly, which triggers cognitive anxiety in students, but should instead emphasize the depth of solution guidance substance and independent understanding assimilation.

For Future Researchers: Future researchers are advised to expand the sample coverage outside Banten Province and use a longitudinal approach to see the continuous effectiveness of the model. In addition, it is also recommended to integrate other student psychological variables, such as academic self-efficacy or intrinsic motivation, as moderating variables..

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Conflict of interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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