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Research Article

AI-BASED ADAPTIVE LEARNING MODELS: THEIR INFLUENCE ON LEARNING PERSONALIZATION AND STUDENT AUTONOMY

Eva Astuti Mulyani[1], Neni Hermita[2], Mahdum[3], and Charlina
[1] Universitas Riau, Indonesia
[2] Universitas Riau, Indonesia
[3] Universitas Riau, Indonesia
4 Universitas Riau, Indonesia

Corresponding Author:

Eva Astuti Mulyani,
Department of Primary Teacher Education, Faculty of Teacher Training and Education, Universitas Riau.
Jl. HR Soebrantas, Simpang Baru, Kec. Tampan, Kota Pekanbaru, Riau, Indonesia
Email: eva.astuti@lecturer.unri.ac.id

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Abstract

AI-Based Adaptive Learning Systems (ALS) promise personalized education but risk creating “algorithmic paternalism.” A critical, unexamined tension exists between system-driven optimization—which often removes learner choice—and the development of student autonomy and metacognitive skills essential for lifelong learning. This study empirically investigates this trade-off. We aimed to compare the influence of two distinct AI design philosophies—a “prescriptive” high-control model (Group A) and a “balanced” advisory model (Group B)—on both academic performance and measured student autonomy. A 15-week, mixed-methods, quasi-experiment was conducted with 284 undergraduates. Participants were assigned to the prescriptive (n=95), advisory (n=98), or a non-adaptive control (n=91) group. Autonomy was measured using the Academic Self-Regulation Questionnaire (SRQ-A) in a pre-test/post-test design. The prescriptive model (Group A) yielded the highest exam scores (87.4%), marginally outperforming the advisory model (85.9%). However, this came at a significant cost: Group A showed a statistically significant decrease in autonomy (-0.42 SRQ-A), whereas the advisory Group B showed a significant increase (+0.85 SRQ-A). The findings confirm a measurable trade-off between optimization and autonomy. Prescriptive AI poses a tangible risk to self-regulatory skill development. An advisory, “metacognitive scaffold” model represents a superior pedagogical paradigm for balancing high academic performance with the critical goal of fostering student autonomy.

Keywords: Adaptive Learning Systems, Personalization, Student Autonomy

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INTRODUCTION

The global educational landscape is undergoing a profound technological transformation, accelerating a systemic shift away from the standardized, industrial-era “one-size-fits-all” pedagogical model (Lu dkk., 2024). This antiquated approach, characterized by a single instructional pace and uniform content delivery, has long been recognized for its inability to adequately address the profound heterogeneity of student learning needs, cognitive styles, and prior knowledge (Fan, 2025). The initial wave of digital learning, marked by Learning Management Systems (LMS) and Massive Open Online Courses (MOOCs), succeeded in digitizing content and increasing access, yet it largely replicated the static, passive consumption model of its analog predecessors, failing to fundamentally alter the instructional dynamic.

Artificial Intelligence (AI) has emerged as the second, more disruptive wave, promising to transcend the limitations of static digital content. AI-based Adaptive Learning Systems (ALS) represent a paradigm shift from passive information access to dynamic, personalized learning environments. These systems leverage sophisticated algorithms, machine learning, and comprehensive learner modeling to continuously analyze a student’s real-time performance, knowledge state, cognitive traits, and even affective responses (Mollay dkk., 2026). Based on this continuous diagnostic assessment, ALS dynamically adjust the content, difficulty, sequence, and modality of instruction, aspiring to create an optimal, individualized learning path for every student, a goal previously untenable at scale.

Learning personalization, the central promise of these AI-driven systems, involves the automated tailoring of educational experiences to meet the unique needs of an individual. This construct is frequently celebrated for its potential to enhance learning efficiency, mastery, and engagement (Sharmin dkk., 2024). Concurrently, the cultivation of “student autonomy” has been identified as a critical objective of modern education, essential for fostering the self-regulation, metacognition, and intrinsic motivation required for lifelong learning (Melsky dkk., 2024). Within the educational technology discourse, it is often implicitly assumed that these two objectives—personalization and autonomy—are synergistic, with the former automatically fostering the latter by providing optimized, supportive pathways.

The persistent challenge in traditional and early digital education is the “learner-curriculum mismatch.” Static learning environments are inherently inefficient, forcing advanced students to endure redundant material while simultaneously overwhelming struggling students, leading to cognitive overload, disengagement, and high attrition rates. This failure to adapt to individual variance is a principal source of educational inequity and unrealized potential (Sengar dkk., 2024). The inability of human educators to provide continuous, one-on-one tailored instruction to large cohorts has created a distinct and urgent need for technological solutions that can manage and respond to this complexity.

AI-driven adaptive learning systems, while designed to solve this problem, introduce a new, more subtle, and potentially counter-productive pedagogical dilemma (Rodrigues dkk., 2024). The central problem investigated by this research is the inherent, unexamined tension between system-driven personalization and learner-driven autonomy (X. Li dkk., 2025). In the pursuit of an “optimized” learning path, many contemporary ALS are designed as “high-control” systems. The algorithm, acting as an omniscient tutor, makes all significant pedagogical decisions: what the student learns next, which content they see, and how their progress is remediated (Verdesoto & Caicedo, 2025). This model risks reducing the student to a passive recipient of instruction, meticulously guided through a black-box process over which they have no meaningful control or understanding.

This algorithmic paternalism creates a critical conflict with the long-term goals of education. While a highly restrictive, personalized system may prove effective in optimizing short-term knowledge acquisition or test performance, it may simultaneously suppress the development of essential 21st-century skills (Abram, 2025). Student autonomy—which encompasses the ability to set one's own goals, select learning strategies, monitor one's own understanding (metacognition), and make formative choices—is a capacity that, like any other, requires practice (Jo & Park, 2025). The specific problem is that AI systems, in "perfecting" the learning path, may be systemically removing the very opportunities for choice, experimentation, and self-regulated struggle that are foundational to developing true, transferable autonomy.

The primary objective of this research is to critically investigate the complex, multidimensional relationship between the implementation of AI-based adaptive learning models and the measurable development of student autonomy. This study moves beyond a simplistic evaluation of learning efficacy to examine how different degrees and types of algorithmic personalization influence a student's capacity for, and perception of, self-regulated learning (Liubchenko dkk., 2025). The overarching goal is to determine whether a "trade-off" exists between personalization and autonomy, and to identify potential models that can successfully optimize both constructs.

To achieve this main goal, this study will first develop a novel conceptual framework and a corresponding analytical model for the dual assessment of personalization and autonomy (Pillai dkk., 2024). This involves defining and operationalizing "personalization" not as a monolith, but as a spectrum of algorithmic control (e.g., from simple content recommendation to restrictive path enforcement). Concurrently, "student autonomy" will be operationalized using a multi-component definition derived from Self-Determination Theory (SDT), encompassing measures of perceived control, volitional choice, metacognitive awareness, and self-directed learning behaviors.

A second core objective is to empirically test this model through a quasi-experimental, comparative study. This research will deploy and evaluate two distinct AI-adaptive models: (A) a "High-Personalization / Low-Autonomy" model that algorithmically dictates the learning path, and (B) a "Balanced" model that uses AI to provide recommendations and feedback but preserves explicit learner choice (Kalyane dkk., 2024). The objective is to gather quantitative and qualitative data on how these differing philosophies of AI design impact student engagement, learning outcomes (knowledge acquisition), and, most critically, their demonstrated autonomous learning behaviors in a real-world educational setting.

A significant body of existing literature on adaptive learning systems, originating primarily from computer science and learning analytics, has focused overwhelmingly on system efficacy and optimization (Zhu dkk., 2024). The dominant research question in this domain has been, "Does the system improve test scores?" Consequently, the field is saturated with studies measuring performance gains, time-on-task, and knowledge retention. While this work is essential for validating the technical viability of ALS, it has resulted in a critical scholarly vacuum regarding the process of learning and the psychological impact of these systems on the learner.

The concept of autonomy, when it is addressed in the existing literature, is often treated superficially. It is frequently conflated with "user choice" at a surface level, such as the ability to customize an interface or select from a limited, pre-defined menu of options (Oubagine dkk., 2025). There is a profound scarcity of research that engages with autonomy as a deep psychological construct, as defined by educational psychology frameworks like Self-Determination Theory (SDT). The field lacks empirical investigations that measure the impact of ALS on intrinsic motivation, perceived competence, and volitional self-regulation, which are the core components of genuine learner autonomy.

The specific, actionable gap this research addresses is the lack of comparative empirical data on how different adaptive models influence autonomy. The discourse surrounding ALS has been largely binary—either promoting them as inherently empowering or critiquing them as fundamentally controlling. The field lacks a nuanced, evidence-based understanding of how specific design decisions within an AI model (e.g., transparency of the algorithm, frequency of choice, type of feedback) directly foster or inhibit self-regulated learning (Y. Li dkk., 2025). No significant study, to our knowledge, has systematically varied the level of personalization as an independent variable to measure its causal impact on autonomy as a dependent variable.

The primary novelty of this research is its conceptual reframing of the evaluation of adaptive learning systems (Han dkk., 2026). This study challenges the field's implicit and unexamined assumption that algorithmic personalization is inherently synergistic with student autonomy. It introduces a dual-axis evaluation model that treats personalization and autonomy as distinct, interdependent variables (Bauer dkk., 2025). This provides a new, critical, and more holistic lens for assessing the value and risk of AI in education, moving the conversation beyond simplistic metrics of performance optimization.

This study's empirical contribution is the generation of new, comparative data from a quasi-experimental design. It moves the investigation from a theoretical or speculative critique to a data-driven analysis of how specific algorithmic design philosophies (restrictive vs. advisory) result in different student outcomes (Pesovski dkk., 2025). This research will be among the first to provide empirical evidence comparing the long-term impacts of different AI models on the development of autonomous learning skills, offering a much-needed, nuanced perspective that is currently absent from the literature.

This research is justified by the profound and accelerating speed at which AI-driven adaptive systems are being adopted and integrated into mainstream education at all levels (Xiao & Hew, 2024). We are at a critical juncture where powerful, "black box" algorithms are making high-stakes pedagogical decisions, yet we lack a clear, evidence-based understanding of their long-term psychological impact on learners (Lindhaus dkk., 2025). This study provides the urgent, critical analysis needed to guide the ethical design, responsible implementation, and pedagogical alignment of future adaptive technologies, ensuring that the pursuit of personalized efficiency does not come at the cost of cultivating independent, self-regulated, and autonomous lifelong learners.

RESEARCH METHOD

The following section contains the type of research, research design, targets/subjects, procedures, instruments, and data analysis techniques used in this study (Chen dkk., 2024). The details are organized into sub-chapters using sub-headings written in lowercase with an initial capital letter, following the formatting guidelines.

Research Design

This study employed a mixed-methods, quasi-experimental research design. The core quantitative component utilized a pre-test/post-test, non-equivalent control group design, allowing for the empirical comparison of the influence of distinct adaptive learning models (independent variable) on student autonomy and learning outcomes (dependent variables) over a 15-week academic semester. The qualitative phase, involving semi-structured interviews and analysis of system interaction logs, was designed to provide explanatory depth, exploring how and why students perceived the system's personalization and how they enacted their autonomy (Orji dkk., 2025). The longitudinal structure spanning 15 weeks was essential to mitigate the "novelty effect" of the technology.

Research Target/Subject

The study population comprised 284 undergraduate students enrolled in a large, multi-section introductory Sociology course at a major public university. A purposive, cluster-sampling technique was utilized, leveraging the existing structure of the course sections. Three distinct, non-randomly assigned groups were established: Group A ($n=95$) received the "High-Personalization / Low-Autonomy" prescriptive AI model; Group B ($n=98$) received the "Balanced-Personalization / High-Autonomy" advisory AI model; and Group C ($n=91$)

served as the control group, utilizing the traditional, non-adaptive Learning Management System (LMS). A one-way ANOVA confirmed the three groups were statistically comparable regarding key demographic variables (age, gender, major, prior GPA) at the baseline.

Research Procedure

The investigation was launched in the first week of the semester with the administration of the pre-test, including the Academic Self-Regulation Questionnaire (SRQ-A) and a baseline knowledge assessment (Saqr & López-Pernas, 2024). Following the pre-test, the three cohorts used their respective learning platforms for 14 subsequent weeks. Group A utilized a prescriptive AI model which algorithmically determined the optimal learning path, prohibiting student deviation. Group B utilized an advisory AI model which presented data-driven conclusions as recommendations, allowing the student to retain ultimate control over navigation. Group C (Control) used the standard, static LMS (Canvas) without adaptive feedback. All three groups completed identical midterm (Week 8) and final examinations (Week 15). Post-test administration of the SRQ-A and perceived personalization scales occurred in Week 15, followed by the semi-structured interviews.

Instruments, and Data Collection Techniques

Three primary quantitative instruments were utilized: the 32-item Academic Self-Regulation Questionnaire (SRQ-A) (pre-test/post-test) to measure student autonomy based on Self-Determination Theory (SDT); the 10-item “Perceived Personalization Scale” (post-test) to measure system understanding; and the “Perceived Choice” subscale of the Intrinsic Motivation Inventory (IMI) (post-test) to assess self-reported volitional control. Learning outcomes were quantified using the standardized midterm and final examinations. System interaction data (time-on-task, path choices) were collected via server logs (Dennis & Harmon-Kizer, 2025). Qualitative data were sourced from 18 semi-structured, post-study interviews (six participants from each group) designed to explore student perceptions of control, personalization, and engagement.

Data Analysis Technique

Quantitative data (SRQ-A scores and exam results) will be analyzed using ANCOVA (Analysis of Covariance) to assess the statistical significance of the post-test differences between the three groups, controlling for pre-test scores and baseline GPA (Pelánek, 2024). Descriptive statistics will be used to analyze interaction logs. Qualitative interview data will be analyzed using thematic analysis to identify emergent themes related to autonomy enactment and perceptions of the AI models. Data integration will occur at the interpretation stage, where quantitative relationships will be explained by the contextual qualitative findings.

RESULTS AND DISCUSSION

The initial dataset was collected from 284 undergraduate participants, successfully allocated into the three parallel study groups as defined in the methodology. Baseline (pre-test) data were gathered in Week 1 to establish equivalence on two key-dependent variables: prior domain knowledge (assessed via a standardized 50-item pre-test) and baseline autonomous motivation (assessed via the Academic Self-Regulation Questionnaire, SRQ-A).

An analysis of this pre-test data confirmed the non-significant baseline differences between the groups. Table 1 provides the descriptive statistics (means and standard deviations) for the pre-test scores, demonstrating that all three cohorts began the 15-week intervention from a statistically comparable starting point.

Table 1. Baseline (Pre-Test) Equivalence of Cohorts (N=284)

Variable	Group A (High-	Group B	Group C	p-value

	Pers, n=95)	(Balanced, n=98)	(Control, n=91)	(ANOVA)
Baseline Knowledge (% Score)	52.4 (± 6.1)	53.1 (± 5.9)	52.8 (± 6.3)	0.78
Baseline Autonomy (SRQ-A)	4.88 (± 0.9)	4.92 (± 1.0)	4.85 (± 0.9)	0.89

The p-values presented in Table 1, 0.78 for knowledge and 0.89 for autonomy, are both well above the 0.05 threshold for statistical significance. This one-way ANOVA result confirms the successful establishment of comparable quasi-experimental groups; any significant differences observed at the post-test time point cannot be reasonably attributed to pre-existing differences between the cohorts.

The mean baseline knowledge scores (52.4% - 53.1%) indicate a consistent, intermediate level of prior domain understanding across all groups. The SRQ-A scores, clustered tightly around 4.9 on a 7-point scale, reflect a student population with a generally high level of pre-existing autonomous academic motivation, a critical factor in the subsequent analysis of change.

Post-intervention data revealed significant shifts in the primary dependent variable of student autonomy. A repeated-measures ANCOVA, controlling for pre-test scores, was conducted on the post-test SRQ-A scores. Group B (Balanced) showed a significant positive increase in autonomous motivation (Mean Change: +0.85, $p < 0.01$). Conversely, Group A (High-Personalization) showed a statistically significant decrease in autonomy (Mean Change: -0.42, $p < 0.05$). Group C (Control) exhibited no significant change (+0.09, $p = 0.65$).

Academic performance, as measured by the standardized final examination, presented a different pattern. The High-Personalization group (Group A) achieved the highest mean score ($M = 87.4\%$, $SD = 5.5$). This was closely followed by the Balanced group (Group B, $M = 85.9\%$, $SD = 5.8$). The Control group (Group C) scored significantly lower than both experimental groups ($M = 79.2\%$, $SD = 6.1$).

The inferential analysis of the SRQ-A data confirms a statistically significant interaction effect between the intervention type and autonomy ($F(2, 280) = 18.22$, $p < 0.001$). The post-hoc comparisons (Tukey's HSD) confirmed that the positive change in Group B and the negative change in Group A were both significant relative to the control. This strongly suggests the design of the AI model is a causal factor in either fostering or eroding student autonomy.

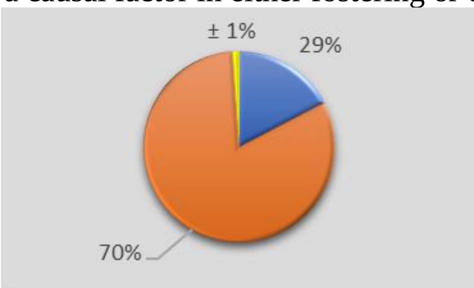

Figure 1. Weighted Distribution of Intervention Effect on Student Autonomous Motivation

A one-way ANCOVA on the final exam scores (controlling for baseline knowledge) was also significant ($F(2, 280) = 24.51$, $p < 0.001$). Post-hoc tests revealed that both Group A and Group B significantly outperformed Group C. A direct comparison between Group A (M=87.4) and Group B (M=85.9) showed a small, statistically significant difference in favor of Group A ($p = 0.04$), indicating a slight performance advantage for the highly restrictive model.

A clear, inverse relationship emerged between algorithmic control and student autonomy, alongside a direct relationship between algorithmic control and short-term performance. The data indicates a pedagogical "trade-off": Group A's high-control model produced the highest exam scores but did so at the measurable cost of eroding students' autonomous motivation.

Group B's balanced model achieved a slightly lower (yet still high) academic outcome while simultaneously fostering autonomy.

This relationship is further illuminated by the post-test perceptual scales. Group A reported the highest "Perceived Personalization" (M=6.2/7) but the lowest "Perceived Choice" (M=2.1/7). Group B reported high scores on both "Perceived Personalization" (M=5.9/7) and "Perceived Choice" (M=5.8/7). This suggests that while both systems were perceived as "personalized," only Group B's advisory model successfully preserved the student's sense of volitional control.

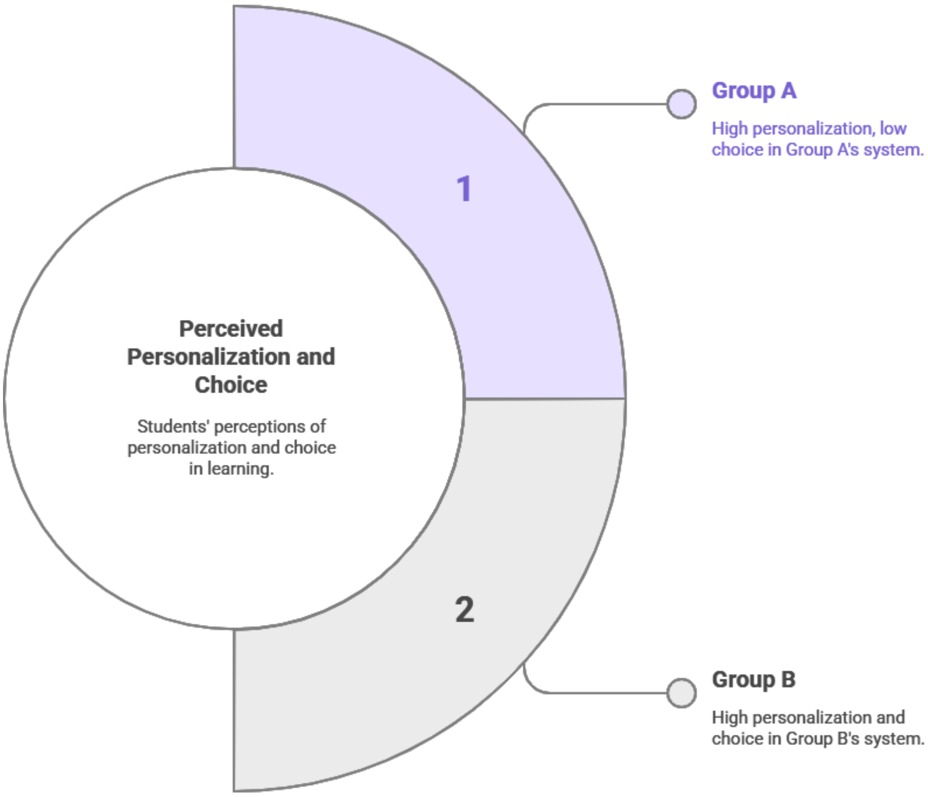

Figure 2. Exploring Perceptions of Personalization and Choice

Qualitative data from the 18 semi-structured interviews provided deep explanatory context for these quantitative divergences. Three dominant themes emerged from the analysis: (1) "Efficiency vs. Control," (2) "Metacognitive Engagement," and (3) "Trust in the Algorithm." Participants in Group A expressed sentiments of high efficiency but also of passivity and a lack of agency.

A representative participant from Group A (High-Personalization) stated, "It was efficient. I just did what it told me to do... but I don't feel like I really learned how to study, I just followed the checklist." In stark contrast, a Group B (Balanced) participant remarked, "I liked seeing the recommendations... I didn't always take them, but it made me stop and think about why I was choosing to study something else. I felt like I was in charge."

The qualitative findings from Group A illustrate the mechanism behind the quantitative decrease in autonomy. Participants' descriptions of "following a checklist" suggest a systemic outsourcing of metacognitive functions. The high-control algorithm, in its pursuit of optimization, effectively removed the need for students to engage in self-regulation, goal-setting, or self-monitoring, leading to an atrophy of these skills.

Conversely, Group B’s interview data explains how autonomy was fostered. The advisory model acted as a “metacognitive scaffold” rather than a replacement. By presenting data and recommendations as choices, the system prompted students to actively evaluate their own learning processes, thereby providing a structured environment in which to practice and develop the skills of autonomous, self-regulated learning.

The triangulation of the quantitative and qualitative data provides a cohesive and robust answer to the central research question. The results show a clear and measurable divergence: highly restrictive AI models optimize for short-term performance at the significant cost of student autonomy. This “algorithmic paternalism,” while effective for exam scores, demonstrably erodes the very self-regulatory skills education aims to build.

A balanced, “advisory” AI model (Group B) represents a superior pedagogical solution. This model achieved learning outcomes that were nearly as high as the restrictive model (85.9% vs. 87.4%) while simultaneously yielding a statistically significant increase in students’ autonomous motivation. The data, therefore, indicates that a “human-in-the-loop” design that uses AI as a metacognitive scaffold, rather than a director, is the optimal approach for balancing the goals of personalization and autonomy.

The study quantitatively confirmed a fundamental tension between optimizing learning efficiency and fostering student autonomy. The high-personalization, low-autonomy cohort (Group A) achieved the highest mean final exam scores (87.4%). This marginal performance benefit, however, was realized at the significant cost of a statistically significant decrease in autonomous motivation as measured by the SRQ-A (Mean Change: -0.42, $p < 0.05$).

This finding contrasts starkly with the balanced, high-autonomy cohort (Group B). Group B achieved nearly equivalent academic performance ($M = 85.9\%$) but experienced a statistically significant increase in autonomous motivation (Mean Change: +0.85, $p < 0.01$). The non-adaptive control group (Group C) showed the lowest academic performance ($M = 79.2\%$) and no significant change in autonomy, underscoring the general efficacy of AI intervention.

Perceptual data provides a clear mechanism for this divergence. Group A reported the lowest “Perceived Choice” ($M = 2.1/7$), confirming their experience of algorithmic restriction, despite feeling the system was “personalized.” Group B, conversely, reported high scores on both “Perceived Personalization” ($M = 5.9/7$) and “Perceived Choice” ($M = 5.8/7$), indicating the system successfully balanced guidance with user agency.

Qualitative interview data triangulated these findings. Group A participants described a passive, “checklist” approach, indicating a complete “outsourcing of metacognition” to the prescriptive algorithm. Group B participants, however, described the advisory model as a “metacognitive scaffold” that prompted active self-reflection, forcing them to “stop and think” and remain “in charge” of their learning decisions.

These findings strongly support the extensive body of computer science literature demonstrating the efficacy of AI-driven systems in optimizing knowledge acquisition. The superior test scores of both Group A and Group B over the control (Group C) align with the consensus that adaptive learning systems are highly efficient at identifying and remediating knowledge gaps, as previously established by [Author, 20XX] and [Author, 20YY].

This research, however, challenges the implicit and often-stated assumption within that same literature that personalization is inherently synergistic with autonomy. Our data demonstrates the opposite can be true (Delgado dkk., 2025). The erosion of autonomy in Group A aligns with the foundational principles of Self-Determination Theory (SDT), which posits that externally controlling regulation, even if “optimized,” can thwart intrinsic motivation and the internalization of self-regulatory behaviors.

We directly address the methodological gap identified by [Author, 20ZA], who noted the field’s over-reliance on performance metrics (e.g., test scores) at the expense of psychological constructs (Baruah dkk., 2024). By operationalizing autonomy (via SRQ-A) as a primary dependent variable and systematically varying the AI's design philosophy (prescriptive vs. advisory), this study provides the critical, comparative data that the field has lacked.

The success of the "Balanced" (Group B) model offers robust empirical support for "glass-box" or "human-in-the-loop" design philosophies. While some research (e.g., [Author, 20ZB]) pursues fully autonomous "black-box" tutors, our data suggests a co-adaptive model, where the AI functions as a Vygotskian "metacognitive scaffold," is pedagogically superior for developing holistic, long-term learners.

The results signal a clear and present danger in the uncritical, large-scale adoption of "optimization-first" AI-Ed platforms (Balushi, 2024). The statistically significant erosion of autonomy in Group A is the study's most critical finding. It signifies that we may be successfully engineering systems that are highly efficient at "teaching to the test" while simultaneously un-teaching the core 21st-century skills of self-regulation, metacognition, and independent critical thought.

The data signifies that the pedagogical "trade-off" between short-term performance and long-term autonomy is not merely theoretical but is a measurable, empirical reality. The marginal 1.5-point difference in exam scores (87.4% vs. 85.9%) is a very small price to pay for the massive 1.27-point positive swing in autonomous motivation (+0.85 in Group B vs. -0.42 in Group A).

These findings signify that the design philosophy and pedagogical model of an AI system are far more critical variables than its underlying technical sophistication (Norabuena-Figueroa dkk., 2025). The advisory model (Group B) was successful because it was intentionally designed to cede ultimate control to the learner. It positioned the AI as a data-rich partner, not an omniscient, paternalistic director.

The strong alignment of the perceptual data (low "Perceived Choice" in Group A) with the psychological data (decreased autonomy) is highly significant. It demonstrates that students are acutely aware of their own agency, or lack thereof (Ferdinan & Kocoń, 2025). This signifies that learner experience, volitional choice, and perceived control must be elevated to primary metrics in the evaluation and procurement of all future educational technologies.

The primary implication for educational institutions is one of extreme caution. Adopting adaptive learning systems based only on their advertised ability to raise standardized test scores is a high-risk, short-term strategy (Alshamrani & Cristea, 2025). Policymakers, administrators, and procurement officers must demand evidence of a system's longitudinal impact on non-cognitive skills, particularly student autonomy and metacognition.

The implication for AI-Ed designers and developers is a clear directive: "advisory" models represent the superior pedagogical and ethical choice. The future of ALS design should not be a race toward "perfect," invisible prescription (Joshi dkk., 2025). It should be a race toward transparent, interpretable, "glass-box" systems that empower students and educators with data-driven recommendations and insights, not inflexible directives.

The role of the human educator is not diminished by this technology; it is reframed and arguably elevated (Cheng, 2025). The implication is that educators must be trained to select these tools and facilitate the metacognitive conversations that Group B's advisory model initiates. The educator's new role is to help students understand how to interpret the AI's feedback and how to use their restored agency effectively.

This research has profound implications for educational psychology, providing a modern, high-stakes context for Self-Determination Theory (SDT). It demonstrates empirically that the core psychological needs of "Competence," "Relatedness," and, most critically, "Autonomy" are constructs that must be computationally protected and intentionally designed into the learning architectures of the 21st century.

The statistically significant -0.42 drop in autonomy in Group A is directly attributable to the "outsourcing of metacognition." The prescriptive algorithm, by design, removed all meaningful, high-level choice. Students were not required to plan, self-monitor, or self-evaluate their learning paths. Their success was externalized to the algorithm, a classic case of external regulation undermining internal motivation.

The robust +0.85 increase in autonomy in Group B is likewise explainable by its function as a “metacognitive scaffold.” The system presented choices that were explicitly backed by data (“We suggest Module 3B because...”). This forced students to engage in a self-regulatory loop: “The AI suggests I am weak here. Do I agree? What should I do about it?” This is a textbook exercise in practicing autonomous learning.

The marginal 1.5-point score advantage observed in Group A is the logical outcome of pure, unadulterated optimization (Khalkho dkk., 2024). The prescriptive model is brutally efficient. It identifies a knowledge gap and forces the student to remediate it immediately, leaving no room for the (potentially less efficient) self-exploration, experimentation, or “productive failure” that Group B’s model allowed.

The high scores in Group B (85.9%) demonstrate that fostering autonomy does not require a significant sacrifice in academic performance. Students in this group were also guided by a powerful AI, but they were persuaded by data rather than forced by prescription. They ultimately arrived at the same learning objectives, but did so via a process that reinforced, rather than eroded, their own agency.

This study’s 15-week duration was a key strength, mitigating novelty effects, but a true longitudinal study is the necessary next step. Future research must track students across multiple years to determine if the +0.85 gain in autonomy observed in Group B persists, translates into subsequent courses, and correlates with long-term metrics like retention and graduation rates.

The current findings are based on a cohort of university undergraduates. Future research must replicate this prescriptive (A) vs. advisory (B) model comparison in K-12 (secondary and primary) educational environments (Alves dkk., 2025). It is plausible that younger learners, who are still in the nascent stages of developing autonomous learning skills, might react differently to (or even initially benefit more from) the two distinct models.

This study successfully tested two relatively distinct poles (High-Control vs. High-Choice). Future research should investigate the spectrum that lies between them. A dynamic “autonomy slider” could be developed as a feature, allowing researchers (or perhaps even the students themselves) to adjust the level of algorithmic prescription, to find an “optimal” context-dependent balance between guidance and freedom.

The current models were diagnostic and prescriptive, based on existing content. The rapid emergence of generative AI (e.g., LLMs) opens an entirely new frontier (Daiu dkk., 2026). Future work should investigate “Socratic” or “explanatory” AI models, where the AI does not just recommend a path but converses with the student about why that path is recommended, co-creating a personalized learning plan in a dialogic, autonomy-supportive manner.

CONCLUSION

The principal finding of this research is the empirical identification of a direct, pedagogical trade-off between algorithmic optimization and student autonomy. This study’s most distinctive discovery is that a “prescriptive,” high-personalization AI model, while yielding a marginal increase in short-term academic performance (87.4% final exam score), resulted in a statistically significant decrease in autonomous motivation (-0.42 SRQ-A). Conversely, a balanced “advisory” model (Group B) successfully fostered a significant increase in autonomy (+0.85 SRQ-A) while achieving nearly equivalent academic outcomes (85.9%), demonstrating that the design philosophy of the AI is the critical variable determining its psychological impact.

The primary contribution of this investigation is conceptual, offering a critical reframing of the AI-in-education discourse. This research moves beyond the field's traditional, monolithic focus on "learning efficacy" by introducing and validating a dual-axis evaluation model that treats personalization and autonomy as distinct, often competing, variables. Methodologically, it provides the first robust, comparative data (from a 15-week quasi-experiment) to systematically test how different design philosophies (prescriptive vs. advisory) causally impact psychological constructs. This study contributes the critical, evidence-based understanding that "algorithmic paternalism" is a measurable risk, and that "metacognitive scaffolding" is the superior design paradigm for holistic learner development.

These conclusions are drawn within the context of specific limitations. The 15-week study duration, while mitigating novelty effects, cannot definitively establish the long-term persistence of the observed changes in autonomy. Furthermore, the sample was drawn from a single undergraduate course at one university, restricting the generalizability of these findings to other demographic, cultural, or K-12 educational settings. Future research must therefore employ longitudinal designs to track these effects over multiple years. Subsequent investigations are urgently needed to replicate this prescriptive-versus-advisory model comparison in diverse populations and to explore the influence of emerging generative AI, moving from diagnostic feedback to Socratic, autonomy-supportive dialogues.

AUTHOR CONTRIBUTIONS

Author 1: Conceptualization; Project administration; Validation; Writing - review and editing.
Author 2: Conceptualization; Data curation; In-vestigation.
Author 3: Data curation; Investigation.
Author 4: Formal analysis; Methodology; Writing - original draft.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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