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AI-Driven LMS: Enhancing Mathematics Education through Generative AI

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Abstract: This research project is expected to develop and test an AI-based Learning Management System (LMS) contents which can promote Self-regulated learning (SRL) with secondary school mathematics students. Considering that conventional LMS have shortcomings in relation to adaptive learning, and given the increasing significance of SRL, this study bridges that gap by proposing new AI-based LMS for mathematics at high school level. Utilizing a Research and Development model combined with an embedding quasi-experiment design of 94 students, the project developed AI-enhanced LMS-based content that included; personalization, adaptive difficulty, AI tutor intervention, and asynchronous administration. The findings reveal that the AI-based LMS content was effective on math students N-Gain scores compared to traditional instruction learning but with small effect sizes. In addition, students employed the AI LMS at moderate-high SRL levels in most of its components (i.e., goal setting, self-evaluation and help seeking). What is new in this work is the development per se (using AI) of LMS content for mathematics to help support SRL, while also taking into account multi-device and user-friendly considerations. Operationally, this AI-LMS system provides a student-centric and flexible learning environment that can help students develop self-regulation of learning to promote engagement and achievement in mathematics. The unique contribution of this study is a validated AI-oriented LMS model that closes the distance between AI promise and SRL requirements in secondary mathematics education.

Keywords: Artificial Intelligence in Education, Learning Management System, Mathematics Education, Self-Regulated Learning

A. Introduction

Self-regulated learning (SRL) has re-emerged as a central construct in contemporary education rather than a mere buzzword. SRL refers to learners' capacity to plan, monitor, and regulate their own learning through goal setting, progress tracking, and strategy adjustment. This intrinsic capability is critical for academic success in modern learning environments that emphasize learner autonomy and proactive engagement (Schunk & Greene, 2017; Jin et al., 2023). Students with strong SRL skills are better

equipped to handle complex tasks, manage their time effectively, seek appropriate support, and develop deeper conceptual understanding, which in turn leads to higher academic achievement (Zimmerman, 2002; Schunk & Greene, 2017). A large body of research has consistently demonstrated positive associations between SRL and academic performance, motivation, and persistence across traditional and online learning settings (Ifenthaler & Yau, 2020).

In parallel, Learning Management Systems (LMS) have evolved from static repositories of digital materials into interactive platforms for delivering and organizing instruction. Early LMSs such as Moodle, Google Classroom, and Edmodo primarily supported basic functions including content sharing, assignment submission, and online discussion (Laohajaratsang, 2018; Yasar & Adiguzel, 2010). While these systems democratized access to learning resources, they remain limited in their capacity to support individual learners and to foster robust SRL. The static architecture of conventional LMS platforms offers minimal adaptation to learners' varied paces, preferences, and prior knowledge. This lack of adaptivity particularly disadvantages students with low SRL competencies, who require responsive scaffolding but often receive little meaningful support from such systems (Jin et al., 2023). The limitations of a one-size-fits-all approach is especially problematic in mathematics, where learners frequently need individualized scaffolding and targeted practice.

Despite the acknowledged importance of SRL and advances in LMS technologies, there is still limited empirical guidance on how AI-driven content within LMSs should be designed to specifically support SRL in secondary school mathematics. The potential of Artificial Intelligence (AI) and Augmented Reality (AR) for enabling personalized learning and strengthening computational thinking and problem-solving in mathematics is increasingly recognized (Nindiasari et al., 2024; Bayly-Castaneda et al., 2024). However, much of the existing work is situated in general or higher education contexts, with relatively little evidence on how AI-driven LMS content influences distinct SRL dimensions such as goal setting, strategy use, self-evaluation, and help seeking during mathematics learning at the secondary level. Moreover, the relationship between students' self-efficacy in using AI-enhanced LMS environments and their overall learning effectiveness in mathematics remains underexplored (Nuangchalerm, 2023; Tandililing, 2011). These gaps highlight the need for design-oriented and empirical studies that articulate clear principles for integrating AI into LMSs to promote SRL in school mathematics.

This study introduces and evaluates AI-driven LMS content specifically designed to foster SRL in secondary school mathematics. Rather than merely embedding AI into a generic LMS, the content was deliberately structured to personalize learning experiences in ways that are sensitive to individual learners' SRL needs (Pellas, 2023). Key features include an AI-tutoring component that provides immediate, tailored

feedback and a "Community" space that facilitates peer support—both of which are central to SRL processes such as help seeking and collaborative problem solving (Winne & Hadwin, 2021). The system is also multi-device and cross-platform (e.g., smartphones, laptops, and various operating systems), enabling flexible access and accommodating diverse technological contexts. Its interface was purposely kept simple and intuitive to reduce extraneous cognitive load and maintain attention on learning tasks (Sweller, 1988). Importantly, the LMS supports asynchronous learning, enabling students to regulate their pace and study time in alignment with core SRL principles.

The primary contribution of this work lies in bridging the conceptual and practical gap between AI capabilities in educational technology and the need to promote SRL in secondary mathematics. By designing and empirically testing a concrete model of AI-based LMS content, the study demonstrates how such environments can be structured to support SRL and improve mathematics achievement. The findings provide empirical evidence for the effectiveness of integrated AI-LMS designs that move beyond content delivery toward cultivating learner autonomy (Wang et al., 2025). Practically, the study offers actionable insights for teachers and curriculum developers on how to embed AI features into LMS platforms to personalize learning, increase engagement, and enhance mathematics performance (Merino-Campos, 2025). More broadly, it contributes to debates on digital transformation in education by illustrating how AI can be harnessed to support student-centered learning models rather than simply digitizing traditional practices.

Based on the identified gaps and the theoretical and practical motivations outlined above, this study addresses the following research question: How does AI-driven LMS content influence self-regulated learning and academic performance in secondary school mathematics?

B. Methods

This study employed a research and development (R&D) approach combined with a quasi-experimental design to develop and evaluate AI-driven LMS content for secondary school mathematics. The instructional design process followed an integrated framework combining the 4D Model (Thiagarajan et al., 1974) and the Prototyping Model (Pressman & R.Maxim, 2015). This hybrid framework was chosen to balance systematic planning with iterative, user-centered refinement.

Define Phase

The Define phase involved a comprehensive needs analysis focusing on SRL challenges and existing LMS use in secondary mathematics. Data were collected on student demographics, access to digital devices (e.g., smartphone ownership, laptop

availability), patterns of online activity, and current use of AI tools for learning. The analysis indicated high overall comfort with technology but limited exposure to specialized mathematics platforms such as Desmos and GeoGebra. This mismatch between students' needs and the limited SRL support within conventional LMSs underscored the need for more adaptive, AI-based tools. The design was theoretically grounded in constructivism (Vygotsky, 1978; Bruner, 1966) and SRL frameworks (Zimmerman, 2002; Pintrich et al., 2000).

Design Phase

In the Design phase, learning objectives, media, and assessment formats were specified, and preliminary prototypes of LMS features were created. Iterative review cycles with prospective users and experts were used to refine interface elements and AI components, including personalized learning pathways, adaptive feedback, and intelligent tutoring functions. These iterations ensured that the design was both pedagogically aligned and technically feasible.

Develop Phase

During the Develop phase, the LMS and its AI-powered content were fully implemented and refined through successive iterations. The system was developed to be multi-device and multi-platform to maximize accessibility. The interface emphasized responsiveness and ease of use to minimize cognitive load and support asynchronous learning. SRL was explicitly targeted by embedding features that promote goal setting, strategy use, self-monitoring, and help seeking (Murray et al., 2013).. Expert validation and pilot testing were conducted to evaluate content quality, usability, and system reliability, with feedback used to adjust both system architecture and learning activities (Dijkstra et al., 2012; Lefortier et al., 2016). Partial Least Squares Structural Equation Modeling (PLS-SEM) was later employed to examine relationships among LMS features, SRL constructs, and learning outcomes.

Disseminate Phase

In the Disseminate phase, the AI-powered LMS was implemented in selected secondary schools and made accessible through a dedicated website. Feedback from students and teachers was systematically collected to refine the system and assess its contextual fit. This phase emphasized the translation of research into practice by ensuring that the developed system contributed to both theoretical advancement and practical improvement in mathematics instruction (Johnson et al., 2022).

A distinctive feature of the system (figure 1) is its support for direct mathematical notation input as an alternative to natural language prompts. Students and teachers can enter complex expressions (e.g., $\int \sin x \, dx$) using an intuitive symbolic keyboard

designed for mathematics (Stacey & MacGregor, 2020). The interface allows users to choose between "Natural Language" and "Math Input," reflecting diverse interaction preferences. The AI assistant, presented with a personalized greeting ("Hi, I'm AIGNITO. How can I help you today?"), offers a humanized interaction while supporting precise, symbol-based queries.

By enabling mathematical notation as a primary input mode, the system reduces ambiguities inherent in text-only prompts and aligns more closely with authentic STEM problem representations. This integration of symbolic computation, AI, and LMS functionality supports deeper conceptual understanding and more accurate AI-generated feedback (Joe Khan Omar Jian, 2023).

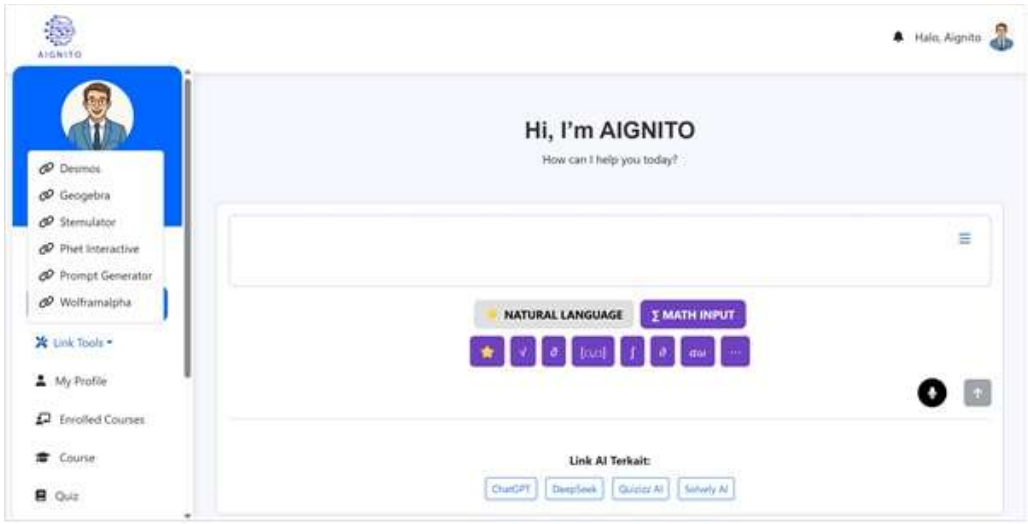

Figure 1. AI Driven LMS

The implementation of the AI-powered LMS, was rigorously assessed through a multi-method approach integrating both quantitative and qualitative measures. The pre-test and post-test served as the foundation for evaluating students' conceptual and problem-solving skills, enabling a comparison of knowledge levels before and after the intervention. The results demonstrated substantial normalized learning gains (N-Gain), with the experimental groups outperforming the control groups, thereby providing empirical evidence of the system's effectiveness in enhancing mathematical learning outcomes. This was further corroborated by the computation of Cohen's d, which yielded large effect sizes across experimental classes, highlighting the educational significance of the intervention.

To capture the students' self-perceptions of learning regulation, the Self-Regulated Learning (SRL) Questionnaire, grounded in Zimmerman's model, was administered. The findings revealed improvements in key SRL dimensions, particularly in goal setting, help-seeking, and self-evaluation. Structural Equation Modeling (SEM) with

Partial Least Squares (PLS) further confirmed that LMS features such as system content, system accessibility, and system feedback exerted strong predictive influences on SRL constructs, which in turn significantly impacted academic achievement. The path model visualization illustrates these complex interconnections, emphasizing how adaptive system design and AI-driven support mechanisms cultivate metacognitive awareness and learner autonomy.

In addition, system usability was systematically measured using the System Usability Scale (SUS). The responses indicated that the LMS was perceived as intuitive, accessible, and responsive, reducing the cognitive burden for learners. This aligns with the platform's design philosophy, as evidenced by the LMS-AI user interface, which integrates both natural language and symbolic mathematical input. This multimodal interaction allowed students to engage with mathematical concepts in a manner that was both personalized and efficient, thereby supporting asynchronous and self-directed learning. The usage logs, automatically recorded by the LMS, provided rich data on learner interactions, participation patterns, and feature utilization. Analysis of these logs revealed that students in the experimental groups engaged more frequently with advanced features such as "Tanya AI" for problem-solving assistance, and community forums for collaborative learning. This behavioral evidence strengthens the claim that the LMS not only enhanced individual learning outcomes but also fostered social and cognitive engagement within a digital learning ecosystem.

Finally, the statistical analyses consolidated these findings. Descriptive statistics mapped the demographic profile of participants, while inferential analyses—including independent samples t-tests—demonstrated significant differences in post-test performance and SRL levels between experimental and control groups. The integration of SEM-PLS added depth by unpacking the latent relationships among system features, SRL constructs, and learning outcomes(Henseler et al., 2015). Collectively, these results underscore the robustness of the AI-powered LMS in advancing both cognitive and self-regulatory dimensions of secondary mathematics learning.

The quasi-experimental evaluation was conducted in two Indonesian secondary schools with a total of 94 students, divided into experimental and control groups across both science and social science streams. The sample comprised four classes: one experimental and one control class in grade XI Science, and one experimental and one control class in grade XI Social Science.

Students in the experimental groups used the AI-enhanced LMS for mathematics instruction, while control groups followed conventional teaching supported by standard LMS or classroom practices. Pre-test and post-test assessments were administered to measure conceptual understanding and problem-solving skills.

Normalized gain (N-Gain) was used to capture learning improvement relative to the maximum possible gain, and Cohen's d quantified the magnitude of the intervention's effect.

Learners' SRL was measured using a questionnaire based on Zimmerman's model, and PLS-SEM was applied to examine how LMS features (e.g., system content, accessibility, adaptivity, feedback) predicted SRL dimensions and academic achievement. System usability was evaluated using the System Usability Scale (SUS), while LMS usage logs were analyzed to characterize interaction patterns and engagement with AI features such as the "Tanya AI" function and community forums.

C. Results and Discussion

The preliminary survey results revealed that the survey was conducted with 805 respondents from Banten and the Special Region of Jakarta, that the vast majority of students (88.4%) owned a smartphone, making it the most common device for accessing digital learning. In contrast, only one-fifth of the respondents reported owning a laptop or notebook (20.2%), and even fewer had access to tablets (5.5%) or home computers (5.5%). Interestingly, 8.4% of students indicated that they did not have any personal digital devices, highlighting a potential barrier to equitable participation in AI-powered learning environments. Despite this limitation, most schools (92.2%) reported providing access to computers for learning purposes, which partially mitigates disparities in device ownership.

In terms of internet usage, the data showed encouraging patterns of digital engagement. While a small proportion of students admitted to rarely (9.7%) or never (0.0%) using the internet for learning, a significant majority reported frequent use. Specifically, 33% used the internet occasionally for academic purposes, 40.4% reported using it often, and 16.4% indicated that they always relied on the internet to support their studies. These findings suggest that students are not only digitally connected but also accustomed to integrating online resources into their learning routines. However, the variation in device ownership and frequency of internet use underscores the importance of designing LMS platforms that are mobile-friendly, low-bandwidth compatible, and inclusive of students with limited digital access.

The survey results revealed interesting patterns in students' use of digital tools to support their learning. When asked about search engines, a majority of students reported relying on them regularly: 31.3% stated they often used search engines, while 35.4% used them occasionally, and 9.4% reported always using them. Only a small portion indicated rare use (20.6%) or never using them at all. This highlights the critical role of search engines in modern learning routines, functioning as students' primary gateway to information.

In terms of AI-assisted learning, the responses indicated a slightly more cautious adoption. About one-third of the students (33.9%) reported using AI tools such as ChatGPT, DeepSeek, or Gemini occasionally, while 16.3% claimed to use them frequently. However, 18.6% admitted to never using AI for learning, and 26% indicated rare use. This suggests that while AI integration in education is emerging, it is not yet as universal as the use of search engines, reflecting both the novelty of the technology and possible hesitations regarding trust, accuracy, or accessibility.

The reasons behind students' use of AI further illuminate its perceived educational value. The most common motivations were to help explain subject matter (53.4%), complete assignments (48.1%), and generate ideas or summaries (46.1%). A smaller percentage reported using AI out of curiosity or experimentation (12.9%), while 9.1% indicated they did not use AI at all. These findings suggest that students see AI primarily as a supportive learning assistant helping them clarify concepts, structure responses, and manage academic tasks rather than merely a tool for casual exploration. Such patterns emphasize the growing role of AI in shaping learners' study practices and highlight its potential to foster deeper engagement when integrated into structured educational systems.

The survey results highlight students' preferences when encountering learning difficulties. Nearly half of the respondents reported turning to teachers (48.7%) or peers (48.6%) as their primary sources of support, underscoring the continued importance of human interaction and social learning in education. At the same time, a considerable proportion of students sought help through digital means, with 41.5% using search engines such as Google and 28.9% relying on AI-based tools like ChatGPT or Copilot. Interestingly, 31.4% still preferred consulting books, indicating that traditional resources remain relevant alongside modern technologies. These findings suggest that while students increasingly adopt digital tools for learning assistance, interpersonal and conventional supports continue to play a central role in their study practices.

When asked about their comfort level with search engines for learning, the majority expressed positive attitudes. Over 61% of students rated their comfort at levels four or five on a five-point scale, with 34.8% choosing the highest rating. This demonstrates that students not only frequently use search engines but also feel confident in navigating them to locate academic materials. Such comfort with digital tools implies a readiness to transition into AI-powered learning environments, where search-like features and intelligent support systems can be seamlessly integrated into students' existing study habits.

The findings underscore several important pedagogical implications. First, the fact that nearly half of the students still prefer asking for help from teachers (48.7%) or peers (48.6%) when struggling with learning material demonstrates that human

interaction remains central to the learning process, even in a technology-driven environment. This suggests that AI-powered LMS platforms should not be designed to replace teachers or peer collaboration, but rather to complement them by creating hybrid spaces where human guidance and digital assistance coexist. Second, the considerable reliance on search engines (41.5%) and AI tools (28.9%) indicates that students are already integrating digital resources into their learning strategies. Educators can leverage this habit by explicitly teaching students how to critically evaluate information retrieved online and how to use AI responsibly to support problem-solving and conceptual understanding. Such digital literacy training is essential to ensure that students do not simply consume answers but also engage in deeper learning processes. Third, the high comfort level with search engines (over 61% reporting strong confidence) highlights an opportunity for schools to align AI-based LMS features with students' existing practices. Embedding intuitive, search-like interfaces and conversational AI assistants within LMS environments can ease the transition to AI-supported learning by meeting students where they already feel most comfortable.

The analysis of effect size (Cohen's dz) across the four groups revealed consistently strong learning impacts, with notable variation between experimental and control classes. As shown (figure 2) in the combined effect size plot, the experimental groups (G11 Science 2 and G11 Social 2) achieved substantially higher values (dz = 1.31 and dz = 1.32, respectively) compared to their control counterparts (G11 Science 1, dz = 0.96; G11 Social 1, dz = 0.92).

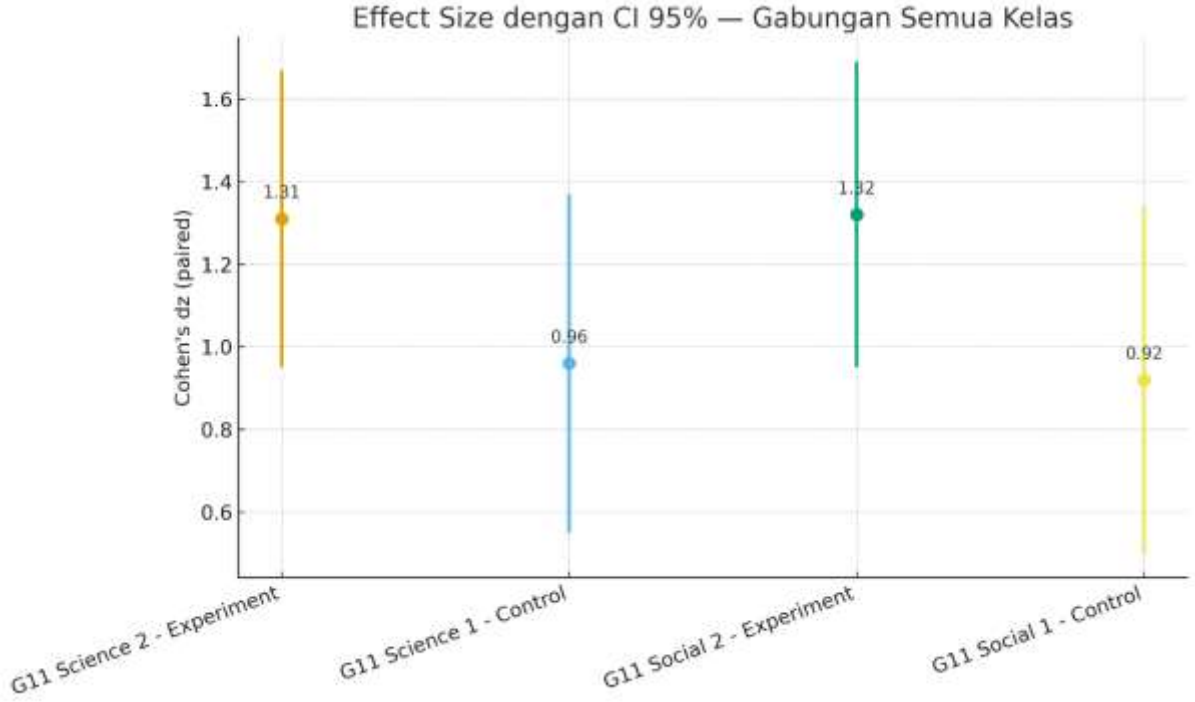

Figure 2. Effect Size (Confidence Interval 95% (CI 95%)

According to Cohen's conventional benchmarks, values above 0.80 are considered large, indicating that the AI-powered LMS intervention had a pronounced impact on students' mathematical learning outcomes. The narrow confidence intervals further support the robustness of these results, suggesting that the observed gains are not merely statistical artifacts but reflect meaningful educational improvements. These findings align with previous research emphasizing the transformative role of adaptive and personalized digital learning environments in enhancing student engagement and performance (Cohen, 1988)(Scherer et al., 2021; Bond et al., 2022).

In the Science experimental class, the structural equation modeling results demonstrated that the LMS intervention explained a substantial proportion of variance in several Self-Regulated Learning (SRL) dimensions and learning outcomes. The most pronounced predictive strengths were observed for help seeking ($R^2 = 0.778$, strong) and learning achievement ($R^2 = 0.724$, strong), indicating that the system effectively encouraged students to actively seek support while also directly enhancing their academic performance. Conversely, dimensions such as emotion and experience ($R^2 = 0.140$, low) and task strategies ($R^2 = 0.027$, very low) exhibited weaker explanatory power, suggesting that while the system facilitated instrumental SRL behaviors, affective and strategic dimensions may require more targeted scaffolding. These findings highlight the need for AI-driven learning designs to integrate not only cognitive and behavioral supports but also motivational and emotional regulation components (Zimmerman, 2008; Heikkinen et al., 2023).

In the Social experimental class, the analysis revealed strong predictive capacities for LMS-related system components, particularly system content ($R^2 = 0.588$), system accessibility ($R^2 = 0.559$), system adaptivity ($R^2 = 0.540$), and system feedback ($R^2 = 0.559$). These results indicate that the design of accessible, adaptive, and feedback-rich learning environments is crucial in supporting students from social science backgrounds, who may have lower baseline proficiency in mathematics compared to science-oriented peers. Importantly, the integrated effect of system content on SRL ($R^2 = 0.422$, medium) underscores that well-structured and contextually relevant learning materials not only transmit knowledge but also cultivate metacognitive awareness and self-regulation. This resonates with recent studies that emphasize the synergistic role of AI-based adaptivity and content personalization in fostering SRL across diverse student populations (Hatta Setiabudhi, S.E et al., 2024; Hair et al., 2019; Winne & Hadwin, 2021). Taken together, these results demonstrate that the AI-powered LMS was effective across both academic streams, though with differentiated impacts: while science students benefited more directly in terms of achievement and help-seeking, social science students derived greater advantages from adaptive system design and content accessibility. This dual pattern suggests that the system's pedagogical affordances align differently with learner profiles, thereby reinforcing the importance of adaptive instructional design tailored to heterogeneous student needs. The strong effect sizes across groups, coupled with substantial R^2 values in core SRL dimensions,

provide robust evidence for the effectiveness of AI-driven LMS platforms in promoting both academic achievement and self-regulatory competencies in secondary mathematics education.

D. Conclusions

This study demonstrates that the implementation of an AI-powered LMS exerts a significant impact on both students' mathematical achievement and the development of Self-Regulated Learning (SRL) skills in secondary education. The analysis of effect sizes (Cohen's dz) revealed that the experimental groups achieved consistently higher gains compared to their control counterparts, with all values exceeding the threshold for a large effect. The narrow confidence intervals further reinforced the robustness and reliability of these results, confirming that the improvements observed are both statistically and educationally meaningful. In the science experimental class, the LMS showed strong predictive power for help seeking and learning achievement, underscoring the system's capacity to foster proactive learner engagement and tangible performance outcomes. However, dimensions such as emotion and experience and task strategies were less strongly influenced, suggesting that affective regulation and strategic learning behaviors may require additional targeted interventions. In contrast, the social science experimental class benefited substantially from LMS features such as system content, system accessibility, system adaptivity, and system feedback. These findings highlight that, for students with relatively lower baseline proficiency in mathematics, adaptive content design and accessible digital infrastructure are critical in supporting SRL development. Taken together, the findings provide compelling evidence that the AI-powered LMS was effective across both academic tracks, though with differentiated impacts. Science students demonstrated more direct benefits in achievement and help-seeking, while social science students benefited more from adaptive instructional design and system affordances. This duality underscores the importance of tailoring AI-driven pedagogical designs to heterogeneous learner profiles. Ultimately, the strong effect sizes and substantial explanatory power across core SRL dimensions attest to the effectiveness of AI-enhanced LMS platforms in fostering both academic achievement and metacognitive growth among secondary school students.

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