Evaluation of an AI-Based Feedback System for Enhancing Self-Regulated Learning in Digital Education Platforms

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Abstract: The development of self-regulated learning (SRL) skills, including the ability to plan, monitor and reflect, is increasingly recognised as essential for academic success in online learning environments. Despite this, most digital learning platforms continue to provide limited feedback, typically focused on task outcomes rather than learning processes. This study investigates the effectiveness of an artificial intelligence-based feedback system integrated into a standard online course platform. The system delivers adaptive, process-oriented feedback by analysing anonymised engagement summaries and short reflective inputs, aiming to promote self-regulated learning strategies without requiring additional instructor involvement or manual input for feedback generation. A quasi-experimental study was conducted with 180 undergraduate students enrolled in a fully online course. Participants were pseudo-randomly assigned by an automated allocation script to an experimental group (n = 90) receiving AI-based adaptive feedback or a control group (n = 90) with standard LMS features. The system employed behavioural indicators (e.g., time-on-task, quiz activity and content engagement) and natural language analysis of reflective entries to generate personalised prompts related to goal-setting (including time management), effort regulation and metacognitive reflection. Data sources included post-course surveys, aggregated system interaction records, academic performance data and open-ended student feedback on the system's perceived effectiveness and usability. Students who received adaptive feedback exhibited significantly stronger engagement with SRL behaviours, including earlier task initiation, increased use of optional learning resources and greater consistency in study routines. Qualitative responses indicated that participants found the feedback clear, timely, actionable and supportive of their cognitive and motivational processes. In contrast, control group participants primarily relied on grade-based feedback and exhibited fewer strategic adjustments during the course. The findings suggest that a lightweight, AI-driven feedback mechanism can be effectively integrated into online course platforms to support SRL at scale. This study demonstrates how adaptive AI feedback can meaningfully influence academic outcomes, planning behaviour and engagement with feedback in digital learning environments.

Keywords: Self-regulated learning, Adaptive feedback, Learning analytics, Digital education, Motivation and reflection, Artificial intelligence in education

1. Introduction

Self-regulated learning (SRL) refers to students' ability to plan, monitor and reflect on their learning processes. These skills are essential for success in digital education, where students work independently with minimal guidance (Zimmerman, 2000). Yet most LMSs lack integrated SRL support, offering static, outcome-based feedback (e.g., grades/correctness) without guiding strategy adjustment (Tsai, Whitelock-Wainwright and Gašević, 2020). This limited model undermines SRL, reducing engagement and increasing procrastination (Wolters and Brady, 2021).

Artificial intelligence (AI) offers new opportunities to address these challenges by providing real-time, individualised support that encourages self-directed learning. By analysing engagement indicators, AI-driven systems can deliver timely prompts that foster planning, monitoring and reflection (Cavalcanti et al., 2021; Lim

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et al., 2023). Unlike correctness-based feedback, AI can promote deeper learning by supporting self-regulation. AI-based feedback can operate autonomously, offering consistent, equitable and adaptive guidance at scale (Mejeh, Sarbach and Hascher, 2024). Despite substantial AI-in-education research, many tools target performance rather than underlying SRL mechanisms and address isolated elements (e.g., planning or reflection) instead of the full cycle. Integration into standard LMSs also remains limited. Hence, scalable, interpretable systems are needed to deliver process-oriented feedback across SRL phases with minimal manual input.

To address this gap, the present study focuses on four key SRL components: planning, monitoring, reflection and effort regulation, which together capture the core cognitive, metacognitive and motivational processes of effective independent study. Time management is treated as a behavioural aspect of planning, reflecting students' ability to organise study schedules and control pacing. These components align with Zimmerman's (2000) cyclical model of forethought, performance and reflection. They can also be reliably observed through digital engagement data. Broader SRL frameworks such as those by Pintrich (2000) and Panadero (2017) include motivational and contextual factors, but these are more difficult to capture through learning system data. The selected components therefore provide a balanced and measurable representation of SRL within digital contexts. Planning and effort regulation correspond to forethought and strategic control, monitoring captures ongoing metacognitive awareness, and reflection represents post-task evaluation and adaptation. These frameworks continue to guide current AI-supported SRL research where Zimmerman's and Pintrich's models remain central (van der Graaf et al., 2023; Heikkinen et al., 2025). Building on this theoretical foundation, the present study introduces an AI-powered feedback system designed to operationalise these SRL components within a digital learning environment.

To implement this approach, the system was integrated into a standard online learning platform to support all major SRL phases. It analyses patterns of student engagement and reflective input to generate personalised prompts aimed at fostering planning, time management and reflection. It adapts feedback dynamically based on individual learning behaviours, offering continuous and accessible support throughout the course.

Based on the identified gaps, the study addresses three research questions (RQs) focusing on the effects and perceptions of AI-based feedback for SRL:

RQ1: To what extent does AI-based feedback improve students' self-regulated learning (SRL) behaviours compared to standard platform feedback?

RQ2: Which components of SRL (planning, monitoring, reflection or effort regulation) benefit most from the use of adaptive feedback?

RQ3: How do students perceive the feedback in terms of usefulness, clarity and motivation?

The main goal is to evaluate the effects of adaptive AI-based feedback on students' SRL and academic engagement in online education. The study also examines how feedback clarity, usefulness and motivational value influence students' learning experience.

2. Literature Review

The integration of artificial intelligence into digital education has opened new avenues for supporting self-regulated learning. This literature review synthesises research on self-regulation frameworks, feedback models, AI applications in education and existing gaps to justify the need for intelligent feedback systems (Wong et al., 2018; Crompton and Burke, 2023).

2.1 Self-Regulated Learning Frameworks

Self-regulated learning refers to students' proactive management of their cognitive, metacognitive and motivational processes to achieve learning goals (Zimmerman, 2000). Zimmerman's cyclical model of SRL outlines three phases: forethought (goal-setting, planning), performance (monitoring, strategy use) and self-reflection (evaluation, attribution). Each phase involves distinct strategies, from task analysis to self-assessment (Zimmerman and Moylan, 2009). Similarly, Pintrich's model emphasises four areas: cognition, motivation, behaviour and context, highlighting the interplay of metacognitive and motivational factors (Pintrich, 2000).

These skills are particularly crucial in online learning environments, where students face greater autonomy and fewer external cues (Wolters and Brady, 2021). This autonomy often makes consistent engagement difficult (Broadbent and Poon, 2015). Effective self-regulation strongly predicts academic achievement, yet many students struggle without external support (Panadero, 2017). Traditional digital platforms often fail to provide the scaffolding needed to nurture these abilities, delivering feedback that is static and outcome-focused rather than process-oriented (Tsai, Whitelock-Wainwright and Gašević, 2020; Jansen et al., 2020).

In the context of this study, cognitive and metacognitive regulation are represented by monitoring and reflection. Monitoring captures learners' ongoing awareness of their cognitive strategies and progress while reflection involves the evaluation and adaptation of those strategies after task completion. Together, these processes explain how students regulate learning. In addition, effort regulation is conceptualised as the motivational and volitional dimension of SRL, capturing learners' persistence and ability to sustain engagement when tasks become demanding.

Intelligent tools such as virtual mentors and planning aids have shown promise in activating strategic behaviours by prompting students to reflect, plan or adjust their learning goals (Jones and Castellano, 2018; Karaoğlan Yılmaz, Olpak and Yılmaz, 2018). The present study is conceptually grounded in Zimmerman's cyclical model, complemented by Pintrich's motivational perspective. Planning and effort regulation operationalise forethought, monitoring operationalises performance and reflection captures post-task evaluation and adaptation.

2.2 Feedback Models in Education

Feedback plays a key role in shaping students' cognitive and metacognitive development (Hattie and Timperley, 2007). According to their model, it operates at four levels: task (correctness), process (strategies), self-regulation (metacognitive guidance) and self (motivation). Process- and self-regulation–level feedback are most effective for promoting SRL, as they foster strategic thinking and self-evaluation (Lui and Andrade, 2022). Lui and Andrade's (2022) model further explains that learners process feedback through cognitive, metacognitive and motivational mechanisms, stressing that it should align with students' goals and readiness to support meaningful learning.

Narciss (2013) expanded the understanding of formative feedback through the Interactive Tutoring Feedback (ITF) model, which conceptualises feedback as a multidimensional instructional activity. The model highlights cognitive, diagnostic and motivational functions, emphasising feedback loops that foster self-regulation. Building on this, Panadero and Lipnevich (2022) proposed the MISCA model (Message, Implementation, Student, Context, Agents), integrating cognitive, affective and contextual factors to explain how feedback is perceived, processed and acted upon. Effectiveness depends on message content and learner engagement. Together, these frameworks show that feedback should target process and self-regulation levels rather than task accuracy alone.

In digital education feedback often remains limited to correctness or grading with little personalisation or SRL support (Cavalcanti et al., 2021; Garcia, Falkner and Vivian, 2018). This persists despite improved delivery technologies (Carless and Boud, 2018) and is especially evident in asynchronous formats with minimal instructor input (Araka et al., 2020). AI therefore offers dynamic, process-oriented feedback that supports SRL (Deeva et al., 2021). AI-driven feedback requires flexible, secure platforms ensuring privacy and scalability. For example, a custom distance learning system in Kazakhstan was developed to enhance control over functionality, protection and local adaptation (Rakhmetov et al., 2024).

In general, AI-driven feedback agents, especially those incorporating natural language processing (NLP), have shown potential in promoting student autonomy by offering clear, timely and non-judgemental guidance on performance and self-regulation (Fleckenstein, Liebenow and Meyer, 2023; Karaoğlan Yılmaz and Yılmaz, 2020). However, effectiveness depends on student trust and perceived relevance (Ranalli, 2021), making tone, timing and transparency crucial design factors.

2.3 AI Applications in Education

Artificial intelligence technologies, including learning analytics, adaptive systems and conversational agents, increasingly shape digital education through personalised, real-time feedback (Hooshyar, Pedaste and Yang, 2020; Crompton and Burke, 2023). Dashboards show behaviours such as quiz frequency or time-on-task (Tsai, Whitelock-Wainwright and Gašević, 2020) but they often lack actionable support for strategy adjustment (Cukurova, Kent and Luckin, 2019).

More interactive AI systems, such as chatbots or analytics-based tutors, show promise for supporting SRL processes like planning and reflection (Lim et al., 2023; Glick, Miedijensky and Zhang, 2024). AI-driven planning nudges and real-time feedback loops reduce procrastination and promote more consistent study behaviour (Heikkinen et al., 2025; Moubayed et al., 2020). Many tools focus on performance and are hard to integrate into LMS environments (Molenaar, 2022).

Advances in natural language processing (NLP) and large language models (LLMs) have broadened AI feedback capabilities. GPT-4–based systems providing tiered feedback improve students' reflection and planning in programming courses (Nguyen and Allan, 2024; Somasundaram, Mohamed Junaid and Mangadu, 2020), while NLP-based writing assessment tools enhance student revision and metacognitive awareness (Fleckenstein, Liebenow and Meyer, 2023). Yet full-cycle SRL support remains rare (van der Graaf et al., 2023), with reflection and motivation still under-supported.

This gap highlights the limited focus on metacognitive scaffolding (Azevedo and Gašević, 2019) and the need for more interpretable and context-sensitive feedback mechanisms (Rosé et al., 2019). AI is also used to maintain academic integrity through proctoring technologies monitoring user behaviour and biometric data (Sakhipov, Omirzak and Fedenko, 2025), but such systems raise privacy, stress and transparency concerns.

2.4 Gaps in Existing AI-Supported SRL Tools and Comparative Overview

Despite growing interest in artificial intelligence to support self-regulated learning, several key limitations persist in current systems. Many existing tools focus narrowly on one phase of SRL, such as planning, monitoring or reflection, without supporting the full cycle in an integrated way (van der Graaf et al., 2023; Wong et al., 2018). Feedback also tends to emphasise performance outcomes (e.g., quiz scores) rather than developing strategies such as goal-setting, time management or metacognitive reflection (Cavalcanti et al., 2021; Glick, Miedijensky and Zhang, 2024).

A second gap is integration: many tutoring systems operate as external add-ons, limiting scalability (Järvelä, Nguyen and Hadwin, 2023; Crompton and Burke, 2023). Although behavioural profiling through clustering and trace data is increasingly common (Moubayed et al., 2020), embedding such insight into adaptive feedback within learning platforms remains rare (Bergdahl et al., 2024).

A third limitation relates to the depth of feedback. Few systems provide process- or self-regulation-level guidance (Narciss, 2013; Panadero and Lipnevich, 2022), focusing instead on task correctness or performance metrics. Consequently, learners receive limited support for sustained self-regulation. Another challenge is perception: AI feedback, though objective, may seem less authentic (Zhang et al., 2025; Ranalli, 2021). Students report increased motivation but also concern about reduced human interaction (Fan et al., 2025; Djokic et al., 2024).

To address these gaps, this study introduces a lightweight, scalable AI feedback system that supports all SRL phases within a single LMS-integrated framework. Using K-means clustering and rule-based NLP, it delivers timely, interpretable feedback without complex infrastructure. Table 1 compares selected prior systems by SRL components, AI techniques, data sources and integration levels.

Table 1: Comparison of AI-Based SRL Support Systems

System	SRL Phase(s) Supported	Data Source	AI Method	Feedback Type	Platform Integration
CourseMIRROR (Menekse et al., 2025)	Reflection	Reflective texts	Rule-based NLP	Post-lecture prompts	Mobile app
Chatbot-SRL (Lee, Hwang and Chen, 2025)	Reflection	Chat interactions	Rule-based chatbot	Real-time chat prompts	LMS / website
GPT Tutor (Sun et al., 2025)	Planning, Monitoring, Reflection	Code + interaction logs	LLM (GPT-3.5)	Multi-level real-time feedback	Coding platform
Virtual Mentors (Glick, Miedijensky and Zhang, 2024)	All SRL phases	Planning tool usage	AI virtual agents	Interactive training modules	MS Planner
This Study	All SRL phases	Platform logs + short reflections	K-means clustering + rule-based NLP	Adaptive in-course prompts + dashboard	Native LMS integration

2.5 Synthesis and Conceptual Focus

The reviewed literature reveals persistent limitations: incomplete SRL coverage, weak integration and limited metacognitive feedback. To address these issues, this study focuses on four interconnected components of SRL: planning, monitoring, reflection and effort regulation. Within this framework, time management represents a behavioural aspect of planning, reflecting how students regulate pacing and task scheduling. These elements align with major SRL models (Zimmerman, 2000; Pintrich, 2000; Panadero, 2017).

The components inform both the analytical framework and the AI-based feedback design. Planning and effort regulation represent forethought and strategic control, monitoring reflects active metacognitive awareness during task performance, and reflection involves post-task evaluation and adaptation. The system operationalises these processes within one digital environment, providing adaptive feedback across SRL phases and ensuring theoretical coherence throughout the study.

3. Materials and Methods

This study employed a quasi-experimental design to evaluate the effectiveness of an AI-driven feedback system in enhancing self-regulated learning behaviours.

3.1 Participants and Context

This 10-week study was conducted at Khalel Dosmukhamedov Atyrau University in a fully online, self-paced course using a plugin-compatible learning management system (LMS) with integrated activity logging. A total of 180 undergraduate students took part voluntarily. They were pseudo-randomly assigned to an experimental group (n = 90) receiving AI-based adaptive feedback or a control group (n = 90) with standard LMS features such as grades and brief instructor comments.

All participants completed the same materials independently without synchronous instruction. Instructor involvement was limited to uploading materials and routine grading; AI feedback did not involve instructor input. Baseline equivalence was established via a brief self-report on prior online learning experience (Schunk and Greene, 2017). No demographic data were collected. Participation was voluntary and anonymous; informed consent was obtained during course registration on the platform, where users agreed to the use of anonymised data for research purposes.

3.2 AI Feedback System

The artificial intelligence-based feedback system functions as an autonomous plugin within the institutional LMS. It operates independently of the platform infrastructure and provides adaptive, data-informed feedback that supports students' self-regulated learning. The system delivers personalised and timely guidance that strengthens core SRL processes without direct instructor involvement. The overall workflow is presented in Figure 1.

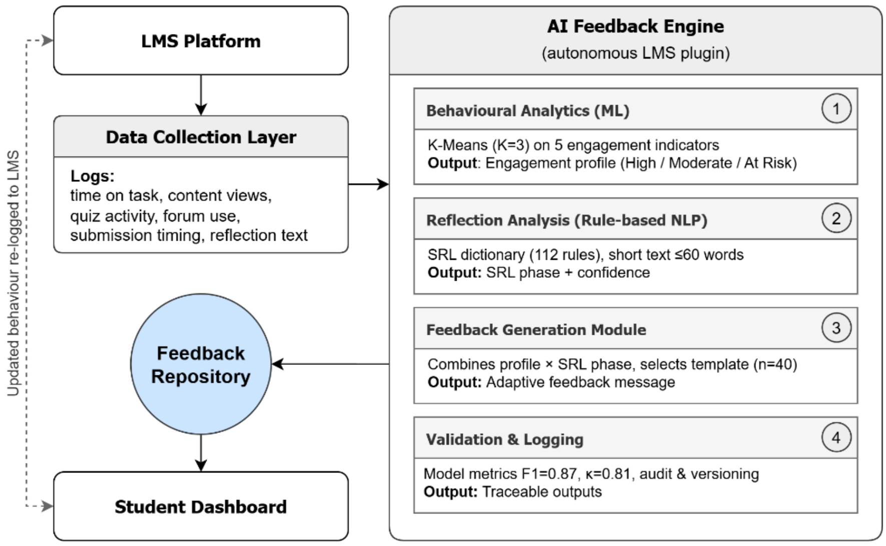

Figure 1: Workflow of the AI-Based Feedback System

The system employs a modular pipeline that combines behavioural analytics, rule-based natural language processing (NLP) and adaptive feedback generation. The data layer consolidates five behavioural indicators, including time-on-task, content interaction, quiz activity, forum participation and submission timing, together with short reflective statements written by students. All processing uses anonymised data within the institution to ensure privacy and compliance.

The behavioural analytics module applies K-means clustering (k = 3) to produce engagement profiles labelled high, moderate and at-risk. Cluster validity was checked with elbow and silhouette criteria. These profiles inform feedback tone, frequency and content. The NLP component analyses short reflections for SRL phase detection. A word limit standardises input and preserves rule precision, since longer texts reduce classification reliability. Reflections are pre-processed and lexically matched to the validated SRL lexicon, then assigned a phase using weighted scoring and confidence estimation; low-confidence results trigger a neutral planning prompt. Representative patterns and implementation parameters are listed in Table 2.

Table 2: Representative Lexical Rules and Implementation Details

Item	Examples / Parameters
Lexical patterns	plan, goal, schedule, check, track, realised, improve, difficult
SRL phases	planning, monitoring, reflection, effort regulation
Lexicon size	112 patterns
Message templates	40 short templates (e.g. “Set one concrete goal for the next 30 minutes”)
Reflection limit	up to 60 words
Clustering	K-means, 3 clusters (high, moderate, at-risk)
Cluster features	time-on-task, quiz activity, content interaction, forum posts, submission timing
NLP scoring	weighted lexical score; confidence threshold 0.6

The feedback module combines each learner’s engagement profile with the detected SRL phase to select one of 40 templates. Tone and frequency adapt to the profile, with rate-limiting to prevent redundancy. All actions are logged with version identifiers for the SRL lexicon, message library and configuration to ensure traceability.

Validated feedback is cached for fast retrieval and delivered in the LMS interface; a dashboard visualises engagement and feedback history. Each interaction updates the record, closing the loop and enabling ongoing refinement aligned with the forethought–performance–reflection cycle. The system functions as an evolving process, not a static recommender, while maintaining interpretability, transparency and reproducibility through explicit rules, validation metrics and documented procedures that support replication.

3.3 Study Design

The study used a quasi-experimental design with pseudo-random assignment to experimental and control groups. Both completed the same 10-week online course. The instructor uploaded materials, graded manually assessed tasks and provided brief comments. The experimental group (n = 90) received adaptive, system-generated feedback with personalised prompts and dashboards; the control group (n = 90) had standard LMS features. Feedback and engagement data were collected in anonymised, aggregated form. A mixed-methods design compared SRL scores, assignment behaviours and performance, and analysed post-course surveys on clarity, usefulness and motivation. Figure 2 summarises the study design and data sources.

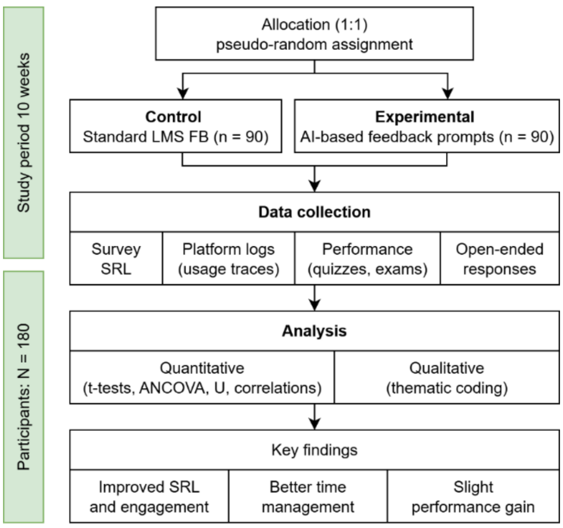

Figure 2: Overview of the Study Design and Data Collection Process

3.4 Analysis Methods

A multi-method analytical framework was adopted to explore the research questions, combining survey data, behavioural logs, academic performance and open-ended responses.

3.4.1 Quantitative analysis

Quantitative data included post-course survey responses and anonymised interaction logs collected via the system's internal dashboard, which summarised engagement behaviours. SRL was measured using adapted subscales from the Motivated Strategies for Learning Questionnaire (MSLQ) (Dent and Koenka, 2016), covering planning, monitoring, reflection and effort regulation. All items were rated on a 7-point Likert scale (1 = strongly disagree; 7 = strongly agree), and composite scores were computed for each construct. Missing values affecting fewer than 5% of cases were handled using mean substitution at the subscale level.

Independent-samples t-tests were used to compare SRL scores, quiz engagement and submission timing between groups. Normality was assessed using Shapiro–Wilk tests; when violated, Mann–Whitney U tests were applied.

In the experimental group, Pearson correlations were used to examine associations between system engagement (e.g., number of feedback prompt responses and dashboard visits) and SRL outcomes. These analyses complemented the between-group comparisons and informed the interpretation of behavioural engagement patterns.

3.4.2 Qualitative analysis

To explore students' experiences with the feedback system, open-ended survey responses were analysed using thematic analysis following Braun and Clarke's (2006) approach. Responses from the experimental group were inductively coded in NVivo to identify recurring themes, including planning, motivation, reflection and perceptions of system value. Two researchers coded the data independently; discrepancies were discussed and resolved to ensure reliability. Responses from the control group were reviewed in parallel to provide contrast and contextualise typical engagement with standard platform feedback. This analysis addressed RQ3 by capturing students' perceptions of the adaptive system's clarity, usefulness and motivational impact (Panadero and Lipnevich, 2022; Ryan and Deci, 2020).

A summary of the main measures and analysis methods used across the study is presented in Table 3, including comparisons of SRL constructs, behavioural indicators, performance outcomes and thematic coding of open-ended responses.

Table 3: Measures and Analysis Methods

Measure	Data Source	Analysis Method
SRL Behaviour Score	MSLQ survey	t-test (Exp vs Ctrl)
Effort Regulation Score		
Submission lead time	System dashboard	Mann–Whitney U
Course performance	LMS gradebook	ANCOVA (covariate: prior GPA)
Prompt responses	Feedback system logs	Correlation (SRL score)
Dashboard views		Correlation (effort score)
Open-ended survey responses	System dashboard aggregates	Thematic analysis (NVivo)

4. Results and Findings

4.1 Quantitative Results

4.1.1 SRL Survey outcomes

Students who received AI-generated prompts showed significantly stronger SRL behaviours than those with standard LMS feedback, particularly in planning and reflection (Table 4).

Table 4: Outcomes for Experimental and Control Groups

Measure	Experimental (M ± SD)	Control (M ± SD)	Test (p-value)	Cohen's d
SRL Behaviour Score (1–7)	5.68 ± 0.52	5.22 ± 0.58	t = 6.47 (p < .001)	0.84
Planning subscale (1–7)	5.85 ± 0.57	5.35 ± 0.65	t = 6.34 (p < .001)	0.82
Reflection subscale (1–7)	5.62 ± 0.64	5.15 ± 0.70	t = 5.43 (p < .001)	0.70
Monitoring subscale (1–7)	5.48 ± 0.60	5.28 ± 0.62	t = 2.54 (p = .012)	0.33
Effort Regulation Score (1–7)	5.80 ± 0.62	5.45 ± 0.68	t = 4.17 (p < .001)	0.54
Exam Score (%)	82.1 ± 9.2	79.3 ± 9.8	F = 3.82 (p = .053)	–
Practice Quizzes (per week)	4.5 ± 1.7	2.9 ± 1.4	t = 7.96 (p < .001)	1.03
Submission Lead Time (hrs)	10.1 ± 9.8	3.8 ± 5.4	U = 672 (p < .001)	–
Late Submissions (number of students)	4	7	–	–

Figure 3 presents a radar chart comparing mean self-regulated learning subscale scores between experimental and control groups. The experimental group outperformed the control group across all dimensions, with the most pronounced differences observed in planning and reflection. Notably, the smaller margin in monitoring suggests that while students became better at planning and evaluating their learning, real-time self-checking remained more difficult to support through asynchronous prompts. The similarity in effort regulation between groups, though still favouring the experimental group, may reflect broader motivational traits less sensitive to system feedback. These profiles illustrate how AI-based feedback influences specific SRL capacities.

Figure 3: SRL Subscale Profiles for Experimental and Control Groups

4.1.2 Learning performance

While exam performance differences between groups were small, students in the experimental group showed a slight advantage. Quiz performance remained comparable across groups. However, students who received adaptive prompts took more optional quizzes, suggesting a stronger focus on mastery.

Controlling for prior GPA, ANCOVA yielded a group effect on Exam Score, $F(1, 177) = 3.82$, $p = .053$, partial $\eta^2 = .021$ (adjusted means: experimental = 81.8%, control = 79.6%). The covariate GPA was significant, $F(1, 177) = 28.94$, $p < .001$. The interaction between Group and GPA was not significant.

4.1.3 Behavioural log analysis

Dashboard data revealed clear differences in learning behaviours. Students receiving adaptive feedback completed more optional quizzes, revisited content more often and spent more time within the LMS platform. These students also submitted assignments significantly earlier than peers in the control group, indicating improved planning and reduced procrastination.

Engagement with the system was consistently high: most students interacted regularly with the personalised dashboard and responded to feedback prompts. Moderate positive correlations were observed between prompt engagement and SRL scores, as well as between engagement and final quiz performance, suggesting that students who engaged more frequently tended to demonstrate stronger self-regulated learning behaviours and slightly higher academic outcomes (Table 5).

Within the experimental group, correlation analysis indicated a modest but clear relationship between prompt usage and SRL scores. As shown in Figure 4, students who responded to a greater number of system prompts generally achieved higher SRL scores. Those who engaged more frequently also tended to report improved planning and reflective thinking, suggesting a deeper adoption of metacognitive strategies.

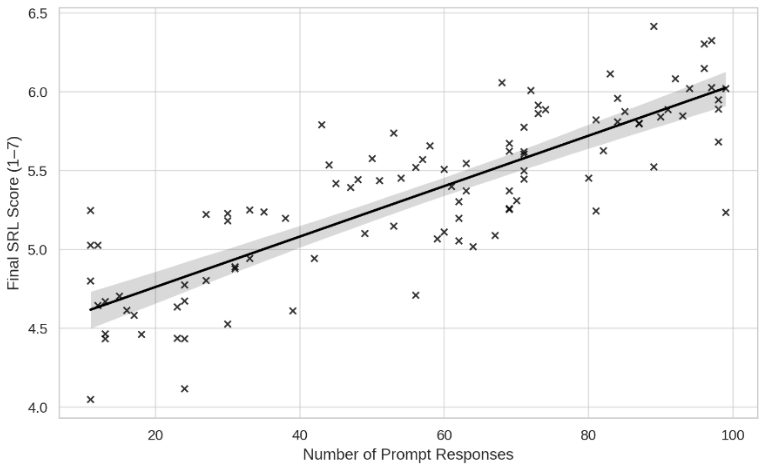

Figure 4: Scatter Plot Showing the Correlation Between Prompt Responses and SRL Score

As shown in Table 5, the number of prompt responses and dashboard views was moderately correlated with SRL behaviour and effort regulation scores. Notably, students who reported stronger learning habits also performed better on the final quiz. These results suggest that consistent engagement supports more effective study strategies.

Table 5: Correlations Between System Engagement, Learning Behaviours and Academic Outcomes

Variable	1.	2.	3.	4.	5.
1. Prompt Responses	1				
2. Dashboard Views	.44**	1			
3. SRL Behaviour Score	.48**	.36*	1		
4. Effort Regulation Score	.40**	.42**	.57**	1	
5. Final Quiz Score (%)	.32*	.28	.45**	.46**	1

Note: * p < .05, ** p < .01. N = 90 (experimental group only).

Figure 5 shows that students receiving improved feedback submitted assignments earlier and more consistently than those in the control group, suggesting better time management and stronger effort regulation. These behaviours indicate more proactive pacing and sustained engagement throughout the course. Students in the experimental group also had fewer late submissions (4 vs. 7), with an average of 540 feedback interactions over 10 weeks and 68% of prompts being viewed or answered.

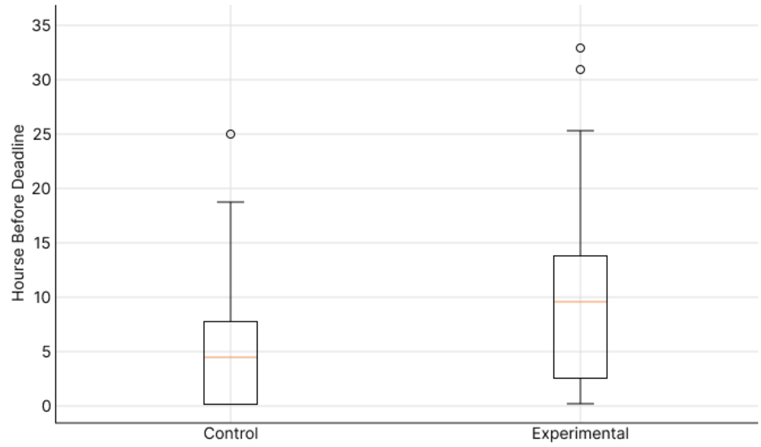

Figure 5: Boxplot of Assignment Submission Lead Time (Experimental vs. Control)

4.2 Qualitative Results

4.2.1 Student perceptions of the feedback system (experimental group)

Thematic analysis of open-ended responses from the experimental group revealed five primary themes. Improved planning and organisational strategies were the most commonly cited benefits, reported by 68% of students. Enhanced reflection and self-awareness were noted by 55% of respondents, with students indicating that the AI feedback system helped them identify learning gaps and adjust study strategies. Increased motivation and reduced anxiety were reported by 38% of students, who valued the regular, supportive prompts. Preferences for system features, particularly the personalised dashboard and feedback visualisation, were mentioned by 35% of participants. At the same time, 20% of students noted limitations, such as repetitive prompts and a lack of gamification features.

4.2.2 Comparison to control group

Engagement levels with the educational platform varied notably between the experimental and control groups (Figure 6). In the experimental group, 38.3% of students reported regular use of the platform, 28.3% used it occasionally and 33.3% minimally. In the control group, only 20% reported regular use, while 55% used it minimally. The question referred to general engagement with the learning platform and course materials, not the feedback tool specifically. However, students in the experimental group noted that the integrated feedback system increased their motivation to log in more frequently and engage with additional resources and tasks.

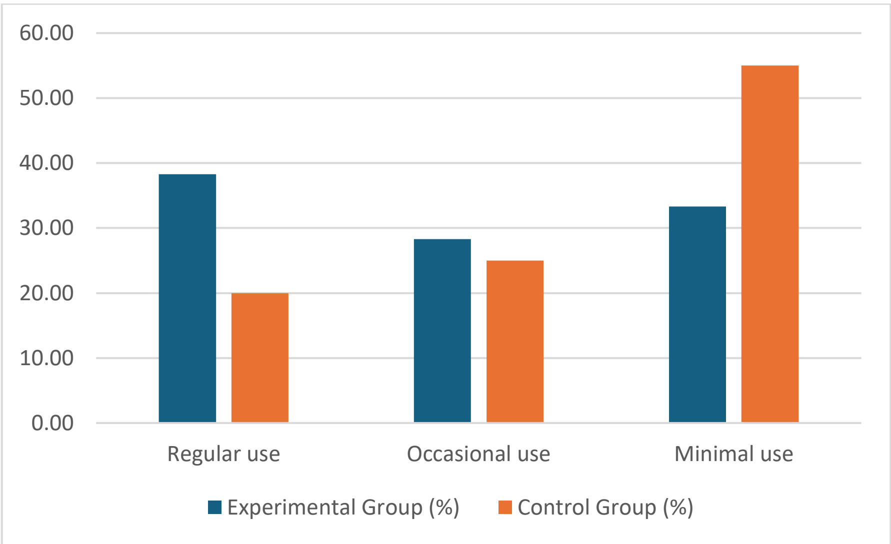

Figure 6: Student Engagement with the Learning Platform (Self-Reported Use Levels)

Analysis of control group responses indicated predominantly passive engagement with feedback. Approximately 70% of students reported primarily checking grades, and 45% read instructor comments without significant subsequent adjustment to their study behaviours. Only 15% of control group participants reported any proactive strategy modification in response to feedback. Several students explicitly expressed a need for more structured, timely and actionable feedback, highlighting the comparative value of the advanced feedback system for supporting self-regulated learning processes.

4.3 Integration of Quantitative and Qualitative Findings

Findings from both quantitative and qualitative analyses were largely consistent. Significant improvements in planning and reflection ($p < .001$) observed in survey data corresponded with behavioural indicators such as earlier task initiation and more frequent use of optional learning resources, reinforcing student reports of enhanced organisation and metacognitive awareness. A smaller but statistically significant gain in monitoring ($p = .012$) mirrored qualitative feedback indicating that students found real-time self-checking more difficult to sustain, even with support. Although the difference in exam performance between groups did not reach conventional significance ($p = .053$), qualitative responses suggested increased perceived preparedness and long-term strategic adjustment.

4.4 Summary of Key Findings by Research Questions

RQ1: Students who received adaptive AI-based feedback demonstrated significantly stronger self-regulated learning behaviours than those with standard LMS feedback ($p < .001$). This included higher scores on planning, reflection and effort regulation, as well as more proactive engagement with optional course components. These results support prior research on the effectiveness of structured, process-oriented support for fostering SRL in online environments.

RQ2: The most substantial improvements were observed in planning and reflection ($p < .001$), consistent across both survey responses and behavioural indicators (e.g., earlier submissions, more consistent engagement). Monitoring gains were present but smaller ($p = .012$), likely due to the inherent challenge of supporting real-time self-checking through asynchronous prompts. These patterns reflect the system's strength in promoting forethought and reflection over in-the-moment regulation.

RQ3: Most students in the experimental group rated the AI feedback as helpful and motivating. In open-ended responses, 68% cited improvements in planning, 55% in reflection and 38% reported reduced anxiety. Students frequently praised the dashboard's clarity, visual design and the supportive tone of the feedback. In contrast, students in the control group described their engagement with feedback as largely passive, with limited strategic response to grades or instructor comments.

Overall, the AI system effectively enhanced students' SRL-related behaviours, especially in planning and time management. While exam score differences were modest, the behavioural and perceptual changes observed suggest that more substantial performance gains could emerge over longer periods of use.

5. Discussion

This study examined the effects of an adaptive feedback system in a fully online course. Findings showed improved SRL, especially in planning, reflection and effort regulation, and students perceived the system as useful, clear and motivating. This section interprets these results, situates them within the literature, proposes an educational model for AI-supported SRL, addresses limitations and outlines implications for practice and future research, contributing to the design of scalable, empathetic AI tools for digital education.

5.1 Enhancing Planning and Reflection through AI Feedback

The AI-based system strengthened self-regulated learning, especially planning, reflection and effort regulation (Glick, Miedijensky and Zhang, 2024; Wong et al., 2018). These gains align with existing research emphasising the value of process-oriented feedback for deepening cognitive and metacognitive engagement (Hattie and Timperley, 2007). Unlike standard platform feedback, the tool supported all key phases of the learning cycle (forethought, performance and reflection) following Zimmerman's model.

Planning improvements appeared in earlier submissions, indicating prompts fostered goal-setting and time management (Heikkinen et al., 2025), and habits consolidated over time, consistent with effects of structured guidance (Bannert, Reimann and Sonnenberg, 2014). Reflection improved as prompts encouraged students to evaluate their learning and adjust strategies, mirroring the effects of effective formative feedback (Lui and Andrade, 2022).

Monitoring gains were smaller, likely due to limits of asynchronous prompts in supporting real-time checks (Lim et al., 2023). These findings highlight the need for more interactive or embedded supports, such as in-task quizzes, to enhance self-monitoring during learning. Although academic performance gains were modest, students who demonstrated stronger SRL behaviours also tended to perform slightly better, suggesting a potential indirect effect. Students' qualitative feedback supported the interpretation of the system as a helpful virtual coach that promoted self-awareness and sustained motivation through clear and consistent guidance (Karaoğlan Yılmaz and Yılmaz, 2020).

5.2 Metacognitive and Motivational Dimensions

The AI-supported tool also helped improve students' motivation by supporting both their thinking and emotional engagement with learning. Students reported higher motivation, less anxiety and better effort management, likely because the feedback felt supportive and non- judgemental (Ryan and Deci, 2020). This aligns with work linking motivation and metacognition (Efklides, 2011). Students who interacted more with the system also showed stronger gains in self-regulation, suggesting that how helpful and well-worded the feedback felt was important (Panadero and Lipnevich, 2022). Some students, however, noted repetitive messages, indicating a need for greater variety and personalisation.

5.3 Proposed Educational Model

Figure 7 presents the educational model that summarises how AI-driven feedback supports SRL. It integrates student characteristics and behavioural data into adaptive mechanisms using clustering and lightweight NLP to generate tailored prompts across all self-regulated learning phases: forethought, performance and reflection. It also represents a continuous-improvement loop, where behavioural and reflective inputs inform subsequent feedback cycles, sustaining alignment between learner behaviour and adaptive guidance.

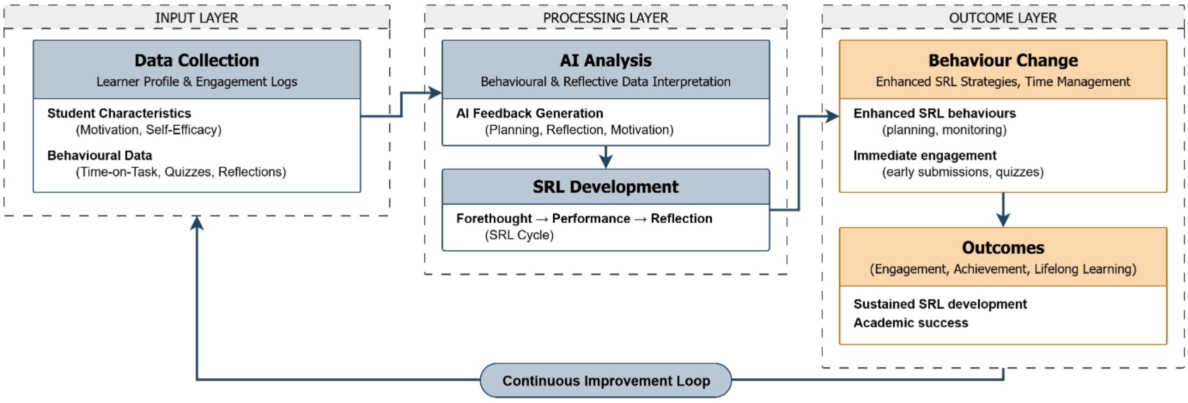

Figure 7: Educational Model for AI-Supported Self-Regulated Learning in an LMS

Through iterative interaction with AI-generated feedback, students progressively refine their planning, monitoring and time management strategies. These behavioural adaptations foster short-term engagement and long-term SRL development. Overall, the model positions AI as a scalable and data-informed mechanism that personalises learning support while maintaining theoretical coherence and system simplicity.

5.4 Connections to Prior Research

The findings of this study extend Zimmerman's cyclical model of self-regulated learning by demonstrating how adaptive AI feedback can operationalise the forethought, performance and reflection phases within an online environment. The empirical evidence supports the view that process-oriented prompts grounded in SRL theory can effectively foster metacognitive engagement and motivational regulation. Consistent with Zimmerman's model, the system supported all phases of SRL (planning, performance and reflection) aligning with evidence that structured, timely prompts can foster metacognitive engagement (Hattie and Timperley, 2007; Panadero, 2017). The results echo prior studies demonstrating the value of adaptive scaffolding in promoting learner autonomy and reducing procrastination (Lim et al., 2023; Heikkinen et al., 2025). Additionally, the positive student perceptions support previous findings on the motivational benefits of non-judgemental, personalised AI feedback (Karaoğlan Yılmaz and Yılmaz, 2020). Unlike earlier systems focused solely on performance metrics, this study highlights the value of integrating behavioural clustering with NLP to deliver lightweight, process-oriented support. This approach directly addresses known limitations in current digital platforms (Cavalcanti et al., 2021; van der Graaf et al., 2023). Together, these results affirm the promise of AI as a scalable tool for fostering effective, student-centred learning strategies in digital education.

5.5 Limitations

While this study provides valuable insights, several limitations must be acknowledged. First, because the study wasn't fully randomised, differences in motivation or engagement might still have affected the results. Second, the sample was limited to 180 participants enrolled in a fully online learning course, which limits how broadly the findings can be applied across other disciplines, educational levels or institutional settings. Third, the 10-week study period may not have been long enough to observe the full development of self-regulated learning habits or their sustained impact on academic performance. Fourth, although effective for individual regulation, the system's logic was static and lacked advanced methods such as semantic personalisation or reinforcement learning for deeper adaptability. Finally, the research addressed only individual learning processes and did not consider socially shared regulation, an important factor in collaborative online learning that merits further exploration.

5.6 Practical Implications

The findings suggest several actionable strategies for improving online learning within educational institutions. Instructors can support students by embedding simple prompts for planning and reflection directly into course materials, particularly in courses with limited real-time teacher interaction. This can help students develop better learning organisation and monitor their progress more effectively. Feedback should be delivered in a supportive, non-judgemental tone, as students responded positively to the coaching style perceived in the AI feedback prompts. Small interactive elements such as quizzes or check-ins can help students assess understanding. Learning platforms can use basic behavioural indicators, like quiz attempts or login patterns, to automatically identify students who may need support and deliver timely prompts. Lightweight systems of this kind are especially useful for large-scale deployment, since they demand little computational power and fit easily into existing learning platforms without major technical upgrades (Fischer et al., 2020). Such systems are feasible even for universities with limited infrastructure or staff.

5.7 Future Research Directions

Building on these findings, future research should explore whether improvements in self-regulated learning are sustained over time and lead to lasting academic benefits. It is also important to examine the applicability of the system across various disciplines, educational levels and institutional contexts to assess its generalisability. Enhancing the system with more advanced natural language processing techniques such as semantic analysis or reinforcement learning could support deeper and more flexible personalisation. In addition, expanding the feedback design to support socially shared regulation of learning (SSRL) may increase the system's effectiveness in collaborative and group-based learning environments.

6. Conclusion

This study evaluated the impact of an AI-driven feedback system embedded in a learning management platform on students' self-regulated learning in a fully online course. The findings show that adaptive, process-oriented feedback significantly improved students' planning, reflection and time management compared with standard platform feedback. Students who received AI-generated prompts-initiated tasks earlier, engaged more frequently with optional resources and reported greater motivation and self-awareness. Gains in monitoring were smaller but positive, suggesting the need for additional in-task scaffolds to strengthen real-time regulation.

The study also extends theoretical understanding of how adaptive AI feedback operationalises self-regulation across cognitive, metacognitive and motivational dimensions. The proposed educational model links engagement analytics with rule-based natural language analysis to deliver transparent and pedagogically meaningful feedback across all SRL phases. This approach provides a practical balance between adaptability, ethical data use and system simplicity, making it suitable for institutional adoption. Practically, the results suggest that integrating such AI tools within existing LMS environments can help educators support learner autonomy without increasing workload. Institutions may use similar approaches to improve equity of feedback and enable early intervention in large online cohorts. Future research should examine the long-term effects of adaptive feedback on sustained SRL behaviours, extend testing across disciplines and explore the inclusion of socially shared regulation features. Overall, the study provides empirical evidence that interpretable AI systems can act as effective and scalable supports for developing independent learning skills, bridging the gap between learning analytics research and real-world educational practice.

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Ethics Statement: Ethical approval was not required for this minimal-risk study, which used anonymised platform logs and voluntary post-course surveys without collection of personally identifying or sensitive data; all participants provided informed consent for the use of anonymised data.

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