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Adaptive Artificial Intelligence – Supported Formative Feedback and The Development of Self-Regulated Learning in Undergraduate Education

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ABSTRACT

The increasing integration of artificial intelligence into higher education has created new opportunities for supporting student learning through personalized and data-driven feedback mechanisms. Among these innovations, artificial intelligence-supported formative assessment systems have attracted growing attention due to their potential to provide immediate, individualized, and continuous feedback that encourages students to take a more active role in managing their learning processes. Despite the growing adoption of these technologies, empirical evidence regarding their influence on learner self-regulation remains limited, particularly in large undergraduate learning environments.

This study examines the impact of adaptive artificial intelligence-supported formative feedback on the development of self-regulated learning behaviors among undergraduate students. In this research, artificial intelligence refers to computational systems capable of analyzing learner performance and engagement data to generate personalized feedback, recommend learning activities, and visualize progress toward learning objectives. Such systems are designed not only to support academic performance but also to foster students' abilities to monitor, evaluate, and regulate their own learning processes.

The study employs a quasi-experimental research design involving 638 undergraduate students enrolled in introductory business and social sciences courses at a large public university. Participants were divided into two groups. The control group received traditional instructor-provided formative feedback, whereas the experimental group used an AI-supported formative assessment platform integrated into the institutional learning management system. The platform delivered adaptive feedback messages, progress indicators, and personalized recommendations intended to support students' self-monitoring and strategic learning behaviors.

The findings indicate statistically significant improvements in several dimensions of self-regulated learning among students who used the AI-supported formative assessment system. In particular, students demonstrated stronger capacities for goal setting, monitoring their learning progress, and adapting study strategies in response to feedback. Qualitative reflections further suggest that personalized and timely feedback enhanced learners' sense of autonomy and increased their confidence in managing academic tasks independently.

At the same time, the study identifies potential challenges associated with AI-supported formative assessment. A proportion of students reported a tendency to rely excessively on automated recommendations, occasionally reducing opportunities for independent reflection and self-evaluation. These findings suggest that while artificial intelligence can effectively support self-regulated learning, its implementation should be accompanied by pedagogical strategies that preserve student agency and encourage critical engagement with feedback.

The paper concludes by proposing design principles for AI-supported formative assessment systems that integrate technological efficiency with reflective learning practices and instructor guidance. Such an approach may contribute to the development of autonomous, self-regulated learners capable of navigating increasingly digital and technology-rich higher education environments.

KEYWORDS: *adaptive feedback; learning analytics; learner autonomy; personalized learning; educational technology; self-directed learning; digital pedagogy; student engagement.*

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1. INTRODUCTION

Artificial intelligence has moved from being a peripheral technological innovation to becoming an increasingly visible component of contemporary higher education. Universities now operate in learning environments characterized by large student cohorts, diverse educational needs, and growing expectations regarding personalized learning experiences. Within this context, the capacity of artificial intelligence systems to process large volumes of educational data and provide immediate feedback has generated considerable interest among both researchers and practitioners. The conversation has gradually shifted from asking whether artificial intelligence should be integrated into higher education toward understanding the conditions under which such technologies contribute meaningfully to student learning.

Among the different applications of artificial intelligence in education, adaptive formative feedback occupies a particularly important place. Feedback has long been recognized as one of the most influential factors affecting learning outcomes and academic achievement. Hattie and Timperley (2007) argued that effective feedback allows learners to understand where they are, where they need to go, and how they can bridge the gap between current and desired performance. More recent developments in educational technology have made it possible to automate parts of this process through intelligent systems capable of generating personalized recommendations, identifying learning difficulties, and visualizing progress in real time.

At the same time, the educational value of artificial intelligence cannot be assessed solely in terms of academic performance or efficiency gains. A growing body of literature suggests that the more fundamental question concerns the influence of these systems on learners' capacity to regulate their own learning processes. Self-regulated learning has emerged as one of the most influential theoretical frameworks for understanding student success in higher education. According to Zimmerman (2002), self-regulated learners are characterized by their ability to set goals, monitor progress, employ appropriate learning strategies, and reflect upon their own performance. These capabilities become particularly important in digitally mediated environments where students are expected to assume increasing responsibility for their own learning trajectories.

The relationship between artificial intelligence and self-regulated learning remains theoretically intriguing and empirically underdeveloped. On the one hand, intelligent feedback systems may support self-regulation by providing timely information, reducing uncertainty, and encouraging metacognitive reflection. On the other hand, excessive dependence on algorithmic recommendations may reduce opportunities for independent judgment and critical self-evaluation. Banihashem et al. (2025) observe that many studies at the intersection of artificial intelligence and self-regulated learning remain conceptually fragmented and frequently focus on technological performance rather than educational processes.

This tension is particularly evident in large undergraduate courses where instructors often struggle to provide individualized feedback to hundreds of students simultaneously. Artificial intelligence appears to offer a practical solution to this challenge. However, the educational

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implications of delegating formative feedback processes to intelligent systems remain insufficiently understood. Existing evidence is largely derived from small-scale interventions, online learning environments, or highly specialized educational contexts, leaving significant questions regarding the transferability of findings to traditional undergraduate settings.

The present study addresses this gap by examining the influence of adaptive artificial intelligence-supported formative feedback on self-regulated learning behaviors among undergraduate students enrolled in introductory business and social sciences courses. Rather than focusing exclusively on academic performance, the study places learner self-regulation at the center of the analysis and investigates whether personalized feedback systems contribute to the development of learner autonomy, metacognitive awareness, and strategic learning behaviors.

The study is guided by three research questions. First, does adaptive artificial intelligence-supported feedback contribute to higher levels of self-regulated learning compared with traditional instructor-provided formative feedback? Second, which dimensions of self-regulated learning appear to be most strongly influenced by adaptive feedback systems? Third, what challenges emerge when students interact with intelligent formative assessment systems over an extended period?

By addressing these questions, the paper contributes to current debates concerning the educational role of artificial intelligence in higher education. It also offers empirical evidence relevant to universities seeking to integrate adaptive technologies while maintaining a commitment to student agency, reflective learning, and pedagogical integrity.

2. LITERATURE REVIEW

2.1 Artificial Intelligence and the Changing Nature of Formative Feedback

The rapid expansion of artificial intelligence applications in higher education has altered long-standing assumptions about assessment and feedback practices. Traditionally, formative feedback has been conceived as a dialogical process in which instructors provide information that helps learners understand the quality of their work and identify strategies for improvement. This perspective is rooted in the broader literature on formative assessment, which positions feedback as an essential mechanism for supporting learning rather than merely evaluating performance. Hattie and Timperley (2007) argued that feedback becomes educationally meaningful when it addresses three fundamental questions: where the learner is going, how the learner is progressing, and what actions are necessary to improve future performance.

Artificial intelligence introduces a different dimension to this process. Instead of relying exclusively on instructor interpretation and delayed responses, intelligent systems can analyze behavioral and performance data in real time and generate personalized recommendations at scale. Wongvorachan et al. (2022) suggest that artificial intelligence has the potential to transform feedback from an episodic activity into a continuous and adaptive process. The increasing sophistication of learning analytics systems enables educational platforms to identify learning patterns, detect potential difficulties, and

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provide individualized guidance that would be difficult for instructors to deliver consistently in large classes.

The educational value of these developments, however, remains contested. Some scholars view intelligent feedback systems as powerful tools capable of increasing learner engagement and supporting differentiated instruction. Hooda et al. (2022) argue that artificial intelligence can significantly improve the responsiveness and personalization of educational environments by providing immediate feedback tailored to individual needs. Others adopt a more cautious position, emphasizing that technological efficiency does not automatically translate into meaningful learning outcomes. The ability of intelligent systems to generate recommendations does not guarantee that learners will interpret, internalize, or use these recommendations productively.

This tension has generated increasing interest in understanding the conditions under which artificial intelligence contributes to learning processes rather than simply automating instructional functions. The issue becomes particularly important when considering self-regulated learning, a construct that emphasizes learners' active participation in planning, monitoring, and evaluating their own educational experiences.

2.2 Self-Regulated Learning as a Foundation for Student Success

The concept of self-regulated learning occupies a central position in contemporary educational psychology because it offers a theoretical explanation for why some students are more successful than others in managing increasingly complex learning environments. Zimmerman (2002) conceptualized self-regulation as a cyclical process involving forethought, performance control, and self-reflection. Within this framework, effective learners establish goals, employ strategies, monitor progress, and adjust their behaviors based on feedback and reflection.

Subsequent research has expanded this understanding by emphasizing the multidimensional nature of self-regulated learning. Pintrich (2004) argued that self-regulation incorporates cognitive, motivational, behavioral, and contextual dimensions that interact dynamically throughout the learning process. Similarly, Winne and Hadwin (1998) described learning as a recursive process in which students continuously compare current states with desired outcomes and modify strategies accordingly.

Panadero's (2017) comprehensive review demonstrated that although various theoretical models differ in terminology and emphasis, they converge around several core assumptions. Self-regulated learners are characterized by intentionality, strategic action, and the capacity for metacognitive reflection. These capabilities have repeatedly been associated with improved academic performance, greater persistence, and increased adaptability in higher education environments.

The increasing digitalization of education has intensified scholarly interest in self-regulation because online and technology-enhanced learning environments require students to assume greater responsibility for organizing and managing their own learning activities. The abundance of information, flexibility of access, and reduction of direct instructor supervision create conditions in which self-regulatory competencies become particularly important determinants of success.

Consequently, educational technologies are increasingly evaluated not only according to their impact on performance outcomes but also according to their capacity to foster self-regulatory capabilities.

DOI: https://doi.org/10.65222/VIRAL.2026.6.36.56

This shift has created fertile ground for exploring how artificial intelligence can support learners' abilities to monitor and regulate their own learning processes.

2.3 Artificial Intelligence and Self-Regulated Learning: Converging and Diverging Perspectives

Recent scholarship has increasingly focused on the relationship between artificial intelligence and self-regulated learning. Banihashem et al. (2025) observe that research at this intersection has grown rapidly, yet the field remains conceptually fragmented. Many studies examine technological affordances without adequately explaining the educational mechanisms through which artificial intelligence may influence learner regulation.

A growing body of evidence suggests that adaptive feedback systems can facilitate several dimensions of self-regulated learning. Khalil et al. (2024) argue that adaptive support mechanisms can improve learners' abilities to monitor progress and make informed decisions about future learning activities. Similarly, Huang et al. (2026), in a large-scale meta-analysis, found that artificial intelligence feedback interventions are positively associated with improvements in self-regulated learning outcomes across various higher education contexts.

Studies focusing specifically on learning analytics have reached comparable conclusions. Romdhoni et al. (2025) report that learning analytics systems can enhance metacognitive awareness by making previously invisible learning processes more transparent to students. Intelligent dashboards, progress indicators, and personalized recommendations provide learners with information that may facilitate self-monitoring and strategic planning.

Research also indicates that students frequently perceive adaptive feedback as a source of autonomy and confidence. Yilmaz et al. (2026) found that students often value generative artificial intelligence feedback because of its immediacy and perceived personalization. The study further demonstrated that students' perceptions of feedback sources significantly influence the educational effectiveness of artificial intelligence interventions.

Yet the literature also reveals several important concerns. The increasing availability of algorithmic guidance raises questions regarding dependency, agency, and critical thinking. Liu et al. (2025) suggest that excessive reliance on artificial intelligence may inhibit the development of independent learning strategies if students begin to treat recommendations as unquestionable instructions rather than informational resources.

A related concern emerges from studies of intelligent assessment systems. Chen and Chen (2026) demonstrated that artificial intelligence can improve self-assessment accuracy, but they also noted that meaningful gains depend on students' willingness to engage critically with feedback rather than passively accept automated suggestions. Similar observations have been made by Hadyaoui and Cheniti-Belcadhi (2026), who argue that artificial intelligence systems should be designed to support socially regulated and collaborative learning processes rather than replace human reflection and interaction.

The literature therefore presents an interesting paradox. Artificial intelligence appears capable of supporting self-regulated learning while simultaneously creating conditions that may undermine learner autonomy if technologies are implemented without sufficient pedagogical guidance.

DOI: https://doi.org/10.65222/VIRAL.2026.6.36.56

2.4 Feedback Literacy and Learner Agency in Technology-Enhanced Education

The concept of feedback literacy offers a useful framework for understanding this paradox. Nicol and Macfarlane-Dick (2006) argued that effective feedback does not simply provide information to learners but actively develops their capacity to self-regulate and evaluate their own performance. Feedback should therefore be viewed as a process of learner engagement rather than a one-way transmission of information.

This perspective is particularly relevant in artificial intelligence-supported environments. The effectiveness of adaptive feedback depends not only on the quality of algorithmic recommendations but also on students' capacities to interpret, question, and use feedback constructively. Educational technologies may provide unprecedented quantities of information, yet information alone does not necessarily promote learning.

Mahapoonyanont and Phinla (2026) observed that intelligent assessment systems produce the strongest educational effects when feedback is integrated with opportunities for reflection and self-evaluation. Similarly, Roodsari et al. (2024) emphasized that learning objective-oriented feedback is most effective when students remain active participants in interpreting and applying recommendations.

These findings suggest that artificial intelligence-supported feedback should not be conceptualized as a substitute for human judgment or pedagogical interaction. Instead, intelligent systems may function as cognitive scaffolds that facilitate reflection and support learners' regulatory capacities.

The intersection between artificial intelligence and self-regulated learning has attracted considerable scholarly attention in recent years. Systematic reviews indicate that AI-supported educational technologies can improve feedback quality, provide personalized learning pathways, and facilitate student engagement with learning activities (Banihashem et al., 2025; Romdhoni et al., 2025). Meta-analytic evidence also suggests that AI-generated feedback may positively influence several dimensions of self-regulated learning, particularly goal setting and self-monitoring (Huang et al., 2026). Despite these promising findings, the empirical literature remains fragmented in several important respects.

First, much of the existing research has focused on technological functionality rather than on the underlying mechanisms through which adaptive feedback shapes learners' regulatory processes. Studies frequently evaluate the predictive accuracy or usability of intelligent systems while devoting less attention to how students internalize and use the feedback provided (Wongvorachan et al., 2022). Second, a substantial proportion of available evidence originates from small-scale experimental settings, pilot studies, or highly specialized disciplinary contexts, limiting the generalizability of findings to large undergraduate learning environments (Khalil et al., 2024). Third, previous research has tended to conceptualize self-regulated learning primarily as an outcome variable rather than as a dynamic process that emerges through continuous interactions between learners, technological systems, and instructional environments (Banihashem et al., 2025).

Another unresolved issue concerns the potential unintended consequences of AI-supported feedback. Emerging studies have suggested that excessive dependence on automated recommendations may reduce opportunities for independent reflection and metacognitive judgment (Yilmaz et al., 2026; Liu et al., 2025). The literature therefore presents a tension between two competing assumptions. On one hand, artificial intelligence can scaffold learner autonomy by providing timely and individualized

DOI: https://doi.org/10.65222/VIRAL.2026.6.36.56

guidance. On the other hand, extensive reliance on algorithmic recommendations may weaken students' capacity to develop independent self-regulatory competencies.

These tensions reveal a clear research gap. There remains limited empirical evidence regarding the extent to which adaptive AI-supported formative feedback contributes to the development of self-regulated learning behaviors in authentic undergraduate settings and how students experience the balance between technological support and learner agency. The present study addresses this gap by examining both the measurable effects of adaptive feedback on self-regulated learning and the subjective experiences that accompany its use.

Drawing upon social-cognitive theories of self-regulation and recent work on AI-supported feedback systems, the study proposes a conceptual framework in which adaptive formative feedback influences self-regulated learning through three interconnected mechanisms: increased feedback immediacy, enhanced metacognitive awareness, and greater opportunities for personalized learning support. At the same time, the framework recognizes that excessive dependence on automated recommendations may moderate these relationships by reducing reflective engagement and independent judgment.

Accordingly, the study is guided by the following research questions:

RQ1: Does adaptive AI-supported formative feedback contribute to higher levels of self-regulated learning among undergraduate students?

RQ2: Which dimensions of self-regulated learning are most strongly influenced by adaptive feedback systems?

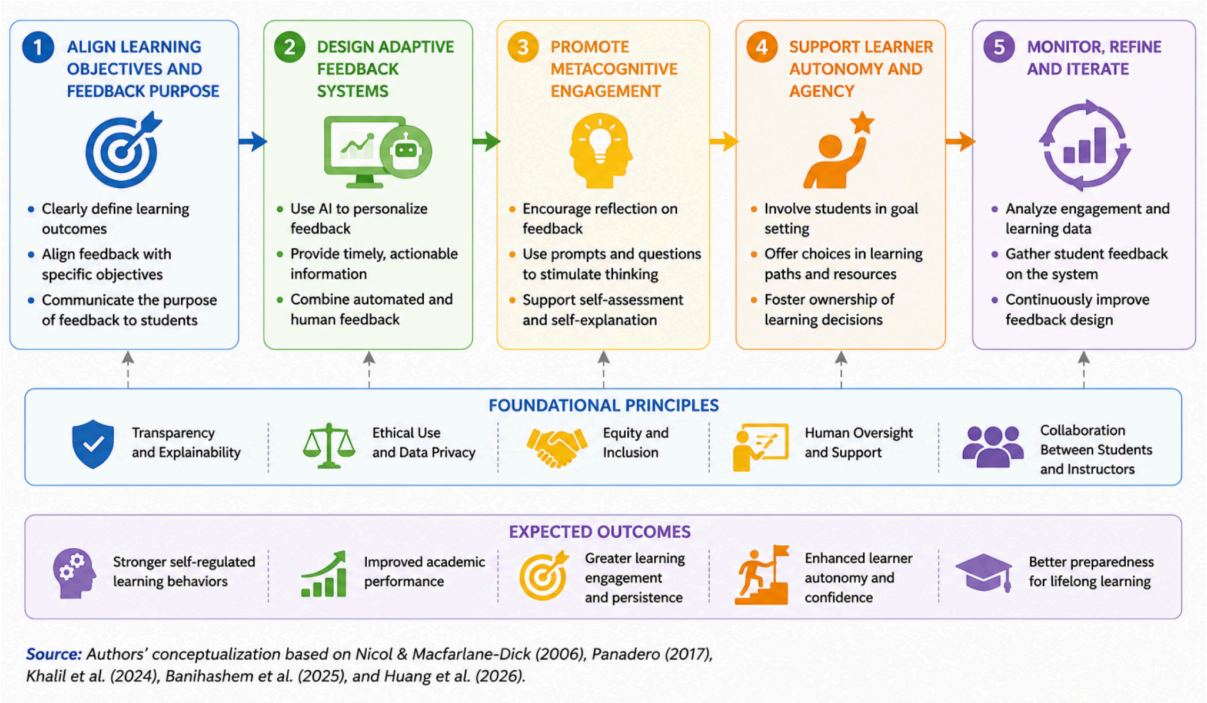
RQ3: How do students perceive the role of artificial intelligence in supporting their learning autonomy and self-regulatory behaviors?

The conceptual model assumes that adaptive feedback functions as an instructional scaffold that facilitates goal setting, monitoring, self-evaluation, and strategic adaptation while simultaneously requiring pedagogical conditions that preserve student agency and reflective learning practices.

The literature suggests that AI-supported formative feedback influences self-regulated learning through iterative cycles of monitoring, reflection, and adaptation. However, existing studies often examine isolated dimensions of self-regulation and rarely provide an integrated representation of the mechanisms through which adaptive feedback supports learner autonomy. Figure 2 presents the conceptual model guiding the present study and illustrates the dynamic relationships between feedback processes and self-regulated learning behaviours.

Figure 1. Conceptual Model of AI-Supported Self-Regulated Learning Processes

DOI: https://doi.org/10.65222/VIRAL.2026.6.36.56



Source: Authors' conceptualization based on Nicol & Macfarlane-Dick (2006), Panadero (2017), Khalil et al. (2024), Banihashem et al. (2025), and Huang et al. (2026).

3. Methodology

This study adopted a mixed-methods quasi-experimental design to examine the influence of adaptive artificial intelligence-supported formative feedback on the development of self-regulated learning among undergraduate students. The methodological approach was selected because self-regulated learning encompasses both observable behaviors and internal cognitive processes that cannot be adequately captured through a single methodological perspective. Combining quantitative and qualitative evidence allowed for a more comprehensive understanding of how students engage with adaptive feedback and how such engagement influences their learning regulation.

The study was conducted during the **2024-2025 academic year at a large public university in Romania**. Participants were enrolled in introductory courses in business administration and social sciences that traditionally involve large student cohorts and extensive use of digital learning platforms.

The **final sample consisted of 138 undergraduate students**. Of these, 68 students formed the control group and received traditional instructor-provided formative feedback through written comments and classroom discussions. The experimental group consisted of 70 students who used an artificial intelligence-supported formative assessment platform integrated into the institutional learning management system.

The allocation of students followed existing course structures and administrative arrangements, making random assignment impractical. Consequently, a quasi-experimental design was considered the most appropriate methodological strategy for examining the intervention under authentic educational conditions while preserving ecological validity.

The artificial intelligence platform was designed to provide adaptive and personalized formative feedback by analyzing learner interactions within the digital environment. The system collected

DOI: https://doi.org/10.65222/VIRAL.2026.6.36.56

information regarding assessment performance, completion of learning activities, time spent engaging with educational resources, and patterns of platform use. Based on these data, the platform generated individualized feedback messages, suggested learning resources, and provided visual representations of learning progress.

The intervention was implemented over a twelve-week academic semester. Students in both groups completed the same instructional activities and assessments. The principal difference between the two conditions concerned the form, frequency, and personalization of formative feedback.

Data collection relied on multiple sources. Quantitative evidence was gathered through a self-regulated learning questionnaire administered at the beginning and at the end of the semester. The instrument was adapted from established self-regulated learning scales and measured five dimensions of self-regulation: goal setting, strategic planning, self-monitoring, self-evaluation, and adaptive strategy use. Responses were recorded on a five-point Likert scale ranging from strong disagreement to strong agreement. Reliability analyses indicated satisfactory internal consistency, with Cronbach's alpha coefficients exceeding the generally accepted threshold of 0.80 for all dimensions.

Additional quantitative data were extracted from the learning management system and included platform access frequency, completion of formative activities, time spent interacting with feedback messages, and use of recommended learning resources. These behavioral indicators provided complementary evidence regarding students' engagement with the adaptive feedback system.

The qualitative component consisted of reflective journals and semi-structured focus groups. Twenty students from the experimental group participated in focus group discussions conducted at the end of the semester. Participants were selected using purposive sampling to ensure representation across different levels of academic performance and engagement with the platform. The discussions explored students' perceptions of personalized feedback, experiences of learner autonomy, and concerns regarding reliance on automated recommendations.

Quantitative data were analyzed using descriptive statistics, independent-samples t-tests, and repeated-measures analyses of variance to examine differences between groups and changes over time. Effect sizes were calculated using Cohen's d to estimate the magnitude of observed effects. To explore the relationship between engagement with adaptive feedback and self-regulated learning outcomes, multiple regression analyses were also performed.

The qualitative data were analyzed through reflexive thematic analysis. Coding was conducted independently by two members of the research team, followed by iterative discussions aimed at refining emerging themes and ensuring interpretive coherence. The integration of quantitative and qualitative findings allowed for triangulation and facilitated a more nuanced interpretation of the relationship between adaptive feedback and self-regulated learning.

Several limitations should be acknowledged. The quasi-experimental design limits the extent to which causal inferences can be established. The study was conducted at a single institution and involved a relatively modest sample size, which may restrict the transferability of findings to other educational settings. In addition, some dimensions of self-regulated learning were measured through self-report instruments and may therefore be influenced by individual perceptions and response biases.

Despite these limitations, the combination of behavioral data, validated self-regulation measures, and qualitative evidence provides a robust methodological foundation for examining how adaptive

DOI: https://doi.org/10.65222/VIRAL.2026.6.36.56

artificial intelligence-supported formative feedback may contribute to the development of autonomous and self-regulated learners in higher education environments.

4. Results and Discussions

Table 1 presents the descriptive statistics for the five dimensions of self-regulated learning measured before and after the intervention. At baseline, no statistically significant differences were observed between the control and experimental groups across any of the measured dimensions, suggesting an acceptable degree of equivalence between groups prior to the implementation of the AI-supported formative assessment system.

Table 1. Descriptive statistics of self-regulated learning dimensions

Dimension	Control Group Pre	Control Group Post	Experimental Group Pre	Experimental Group Post
Goal setting	3.28 (0.62)	3.35 (0.58)	3.31 (0.60)	3.89 (0.54)
Strategic planning	3.22 (0.66)	3.30 (0.63)	3.25 (0.61)	3.81 (0.57)
Self-monitoring	3.11 (0.70)	3.19 (0.65)	3.16 (0.68)	3.95 (0.55)
Self-evaluation	3.27 (0.59)	3.34 (0.61)	3.29 (0.57)	3.84 (0.58)
Adaptive strategy use	3.08 (0.67)	3.15 (0.65)	3.12 (0.69)	3.78 (0.60)

S*ource: Authors' calculations based on survey data (N = 138).*

By the end of the semester, the experimental group demonstrated substantially higher scores across all dimensions of self-regulated learning. The most pronounced changes were observed in self-monitoring and adaptive strategy use. Students who received adaptive AI-supported feedback reported greater confidence in tracking their academic progress and modifying their learning strategies in response to performance information. Improvements in the control group were comparatively modest and did not reach similar magnitudes.

Independent-samples t-tests indicated statistically significant differences between the two groups in post-intervention measures of self-regulated learning. The largest effect sizes emerged for self-monitoring ($d = 0.82$) and goal setting ($d = 0.75$), suggesting that adaptive feedback mechanisms may be particularly effective in supporting students' abilities to observe and regulate their own learning behaviors.

The behavioral data extracted from the learning management system revealed a similar pattern. Students in the experimental group accessed feedback messages more frequently and revisited learning resources more often than students in the control condition. Average weekly engagement with the platform increased progressively during the semester, indicating that students integrated the adaptive feedback tools into their regular study routines rather than using them only immediately before assessments.

Table 2. Student engagement indicators during the intervention

DOI: https://doi.org/10.65222/VIRAL.2026.6.36.56

Indicator	Control Group	Experimental Group
Weekly platform visits	4.2	6.9
Feedback consultations per week	2.1	5.8
Completion of optional learning activities (%)	63.4	81.2
Revisions of recommended resources (%)	41.8	73.5

S*ource: Authors' calculations based on LMS analytics data.*

The quantitative findings suggest that adaptive formative feedback may operate as a form of metacognitive scaffolding. Rather than merely transmitting information about performance, the system appeared to encourage students to engage in processes of monitoring, reflection, and strategic adaptation. This interpretation aligns with the arguments advanced by Khalil et al. (2024), who proposed that adaptive support systems are most effective when they facilitate learners' capacity to regulate their own cognitive and behavioral processes.

To further examine the determinants of self-regulated learning development, a multiple regression analysis was conducted with post-intervention self-regulated learning scores as the dependent variable.

Table 3. Multiple regression analysis predicting self-regulated learning development

Predictor	β	t	p
Frequency of feedback consultation	0.36	4.72	< .001
Use of recommended resources	0.28	3.64	< .001
Time spent interacting with feedback	0.21	2.89	0.005
Prior academic performance	0.14	1.98	0.049

$R^2 = .47$

Source: Authors' calculations.

The model explained approximately 47% of the variance in post-intervention self-regulated learning scores. The frequency with which students consulted adaptive feedback messages emerged as the strongest predictor, followed by the use of recommended learning resources. These findings reinforce the argument that the effectiveness of AI-supported feedback depends not simply on technological sophistication but on the extent to which learners actively engage with the information provided.

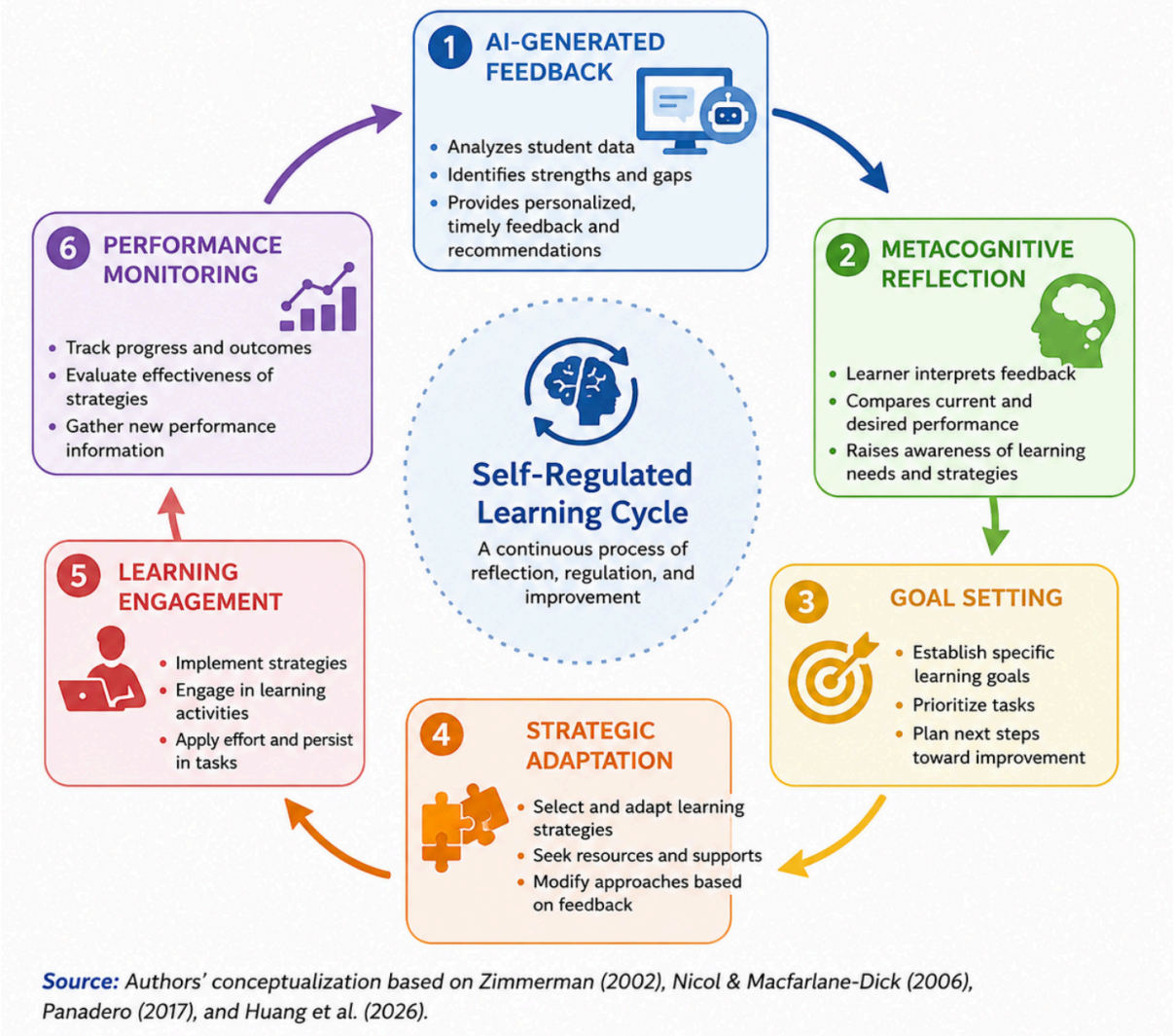
To better illustrate the mechanisms through which adaptive feedback supports learner regulation, Figure 2 presents self-regulated learning as a cyclical process in which artificial intelligence functions as a continuous source of metacognitive prompts and performance information.

Figure 2 conceptualizes self-regulated learning as an iterative and recursive process rather than a linear sequence of actions. Adaptive feedback initiates cycles of reflection, strategic adjustment, and behavioral engagement, which subsequently generate new performance information and additional feedback opportunities. This perspective positions artificial

DOI: https://doi.org/10.65222/VIRAL.2026.6.36.56

intelligence as a catalyst for metacognitive regulation rather than as an autonomous decision-making system.

Figure 2. Cyclical Process of AI-Supported Self-Regulated Learning in Higher Education



Source: *Authors' conceptualization based on Zimmerman (2002), Nicol & Macfarlane-Dick (2006), Panadero (2017), and Huang et al. (2026).*

The qualitative evidence offers a richer understanding of these patterns. Students frequently described the adaptive feedback system as a source of clarity and structure during the learning process. Several participants reported that the personalized recommendations helped them identify weaknesses that might otherwise have remained unnoticed.

One student noted:

> "I usually wait until I receive my grade to realize that I did not understand something. The platform showed me much earlier where I was struggling, and I could do something about it."

Another participant emphasized the role of immediate feedback in supporting learning autonomy:

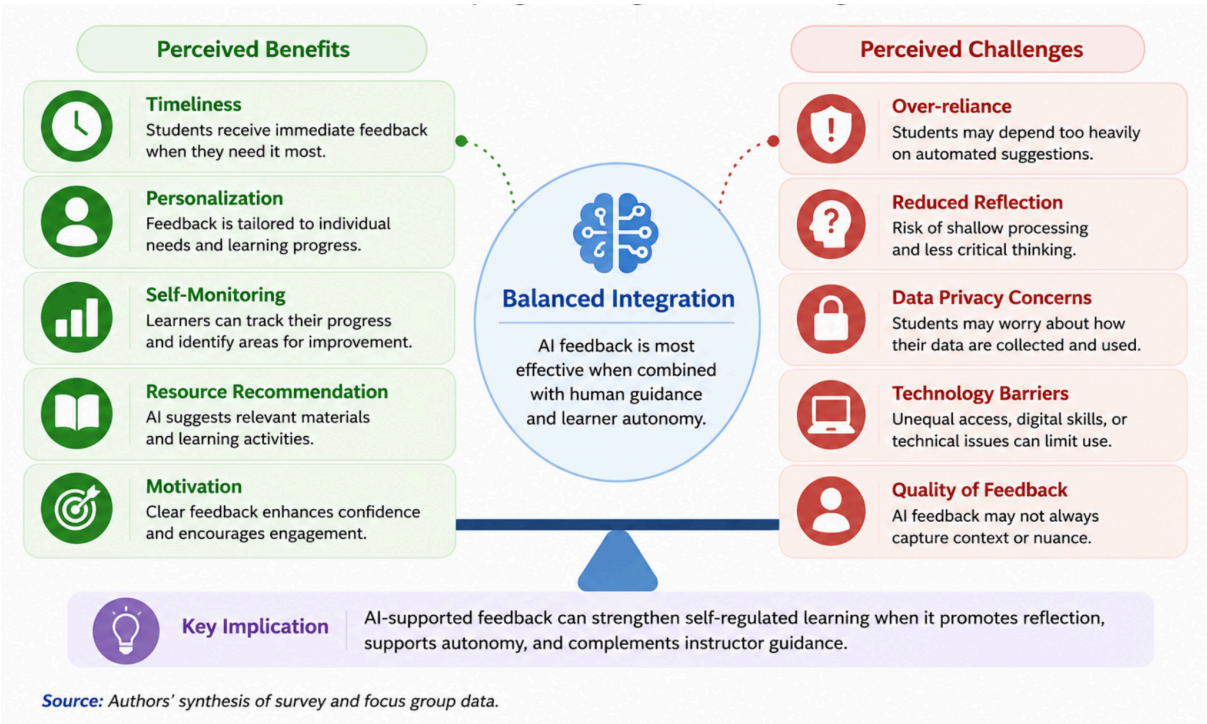
DOI: https://doi.org/10.65222/VIRAL.2026.6.36.56

> "The system did not give me the answers. It helped me understand what I should work on and where I needed to spend more time."

These reflections suggest that adaptive feedback may contribute to a stronger sense of learner agency by making learning processes more visible and manageable.

Although students generally perceived adaptive feedback positively, their reflections revealed a more nuanced picture. The technology appeared to support self-monitoring, motivation, and learning autonomy, while simultaneously raising concerns related to excessive reliance on automated recommendations and reduced opportunities for independent reflection. Figure 3 synthesizes these complementary and competing perceptions.

Figure 3. Perceived Benefits and Challenges of AI-Supported Formative Feedback in Developing Self-Regulated Learning



At the same time, the qualitative findings revealed several tensions. A number of students acknowledged that they occasionally relied too heavily on automated recommendations and followed suggested activities without engaging in deeper reflection about their own learning needs.

As one participant explained:

> "Sometimes I just followed what the system recommended because it seemed easier than deciding for myself."

Another student expressed concern that constant guidance could reduce independent decision-making:

> "The recommendations were useful, but after a while I realized that I was waiting for the platform to tell me what to do next."

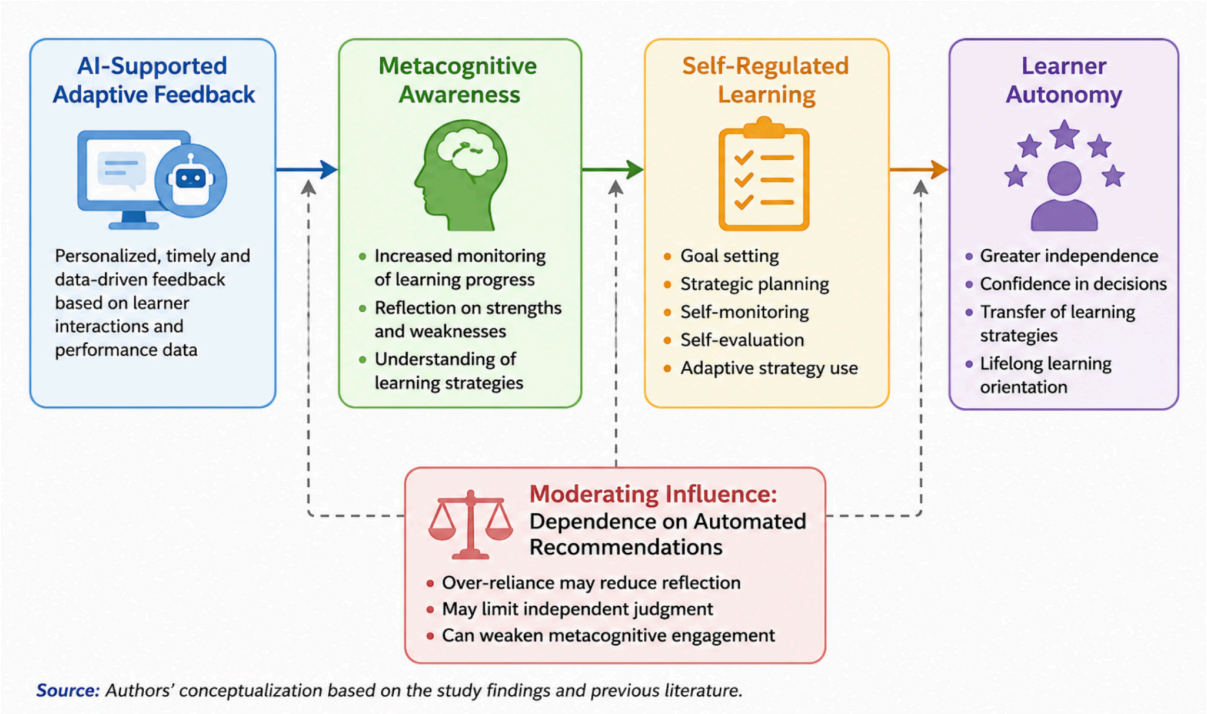
DOI: https://doi.org/10.65222/VIRAL.2026.6.36.56

These observations are consistent with recent scholarship warning that excessive dependence on algorithmic guidance may inadvertently constrain the development of independent metacognitive judgment (Yilmaz et al., 2026; Liu et al., 2025).

Taken together, the findings point to a nuanced understanding of artificial intelligence-supported formative assessment. Adaptive feedback appears capable of strengthening several dimensions of self-regulated learning, particularly those associated with monitoring, planning, and strategic adaptation. However, the educational value of these systems depends on maintaining an appropriate balance between technological support and learner autonomy.

The evidence suggests that artificial intelligence should not be understood as a substitute for reflective learning processes or instructor guidance. Rather, its most productive role may lie in creating conditions that encourage students to become more aware of their learning behaviors while preserving opportunities for independent judgment and self-evaluation. This interpretation supports emerging perspectives that conceptualize AI as a partner in learning regulation rather than as an autonomous instructional agent (Banihashem et al., 2025; Huang et al., 2026).

Figure 4. Conceptual model of AI-supported formative feedback and self-regulated learning development



Source: Authors' conceptualization based on the study findings and previous literature.

5. Conclusions

The increasing presence of artificial intelligence in higher education is changing not only how feedback is delivered but also how students engage with their own learning processes. The findings of

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this study suggest that adaptive AI-supported formative feedback can contribute meaningfully to the development of self-regulated learning behaviors, particularly in relation to goal setting, self-monitoring, and the adaptation of study strategies. Students who interacted with the adaptive feedback system demonstrated stronger capacities to manage their learning processes than those who relied exclusively on traditional instructor-provided feedback.

The results also indicate that the educational value of artificial intelligence extends beyond efficiency gains or automated assessment processes. The adaptive system functioned as a form of metacognitive support that encouraged students to reflect on their progress, revisit learning materials, and engage more actively with formative activities. In this respect, the study contributes to the growing body of literature that views artificial intelligence not simply as an instructional technology but as an instrument capable of supporting learner agency and self-regulation when implemented within appropriate pedagogical frameworks.

At the same time, the findings reveal important limitations and potential unintended consequences. Some students reported a tendency to rely excessively on automated recommendations, occasionally substituting algorithmic guidance for independent reflection and self-evaluation. This observation suggests that the relationship between artificial intelligence and self-regulated learning is not unconditionally positive. While adaptive systems can facilitate the development of self-regulatory competencies, they may also generate new forms of dependency if students begin to perceive algorithmic recommendations as substitutes for their own judgment.

From a theoretical perspective, the study contributes to ongoing debates concerning the integration of artificial intelligence and self-regulated learning by proposing that adaptive feedback should be understood as a mechanism of guided metacognition rather than as an autonomous instructional intervention. The findings support a conceptual model in which artificial intelligence operates through intermediate processes of reflection, awareness, and strategic adaptation. The educational impact of such systems therefore depends not only on the quality of the algorithms themselves but also on how learners interpret and engage with the feedback they receive.

Several practical implications emerge from the findings. Higher education institutions seeking to implement AI-supported formative assessment systems should avoid approaches that position artificial intelligence as a replacement for instructor feedback. Instead, adaptive feedback systems should be designed to complement human guidance and to encourage students to critically evaluate recommendations rather than simply follow them. Educational designers should also integrate opportunities for reflection, self-explanation, and instructor mediation in order to preserve learner autonomy and strengthen metacognitive development.

The study is subject to several limitations that should be acknowledged. The research was conducted within a single institution and involved only undergraduate students enrolled in introductory courses, which may limit the transferability of the findings to other disciplinary or institutional contexts. The quasi-experimental design also restricts causal interpretation, despite the use of comparison groups and longitudinal measurement. Furthermore, the study relied partly on self-reported measures of self-regulated learning, which may be influenced by social desirability and subjective perceptions.

These limitations point toward several promising directions for future research. Longitudinal studies are needed to determine whether the effects of adaptive feedback on self-regulated learning persist over time and whether students transfer these competencies to other learning contexts. Future research should also investigate potential differences across academic disciplines, student characteristics, and varying levels of digital competence. More sophisticated analytical approaches, including structural

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equation modelling and learning analytics techniques, may provide additional insight into the mechanisms through which adaptive feedback influences self-regulation and academic performance.

Ultimately, the study suggests that artificial intelligence can play a constructive role in supporting self-regulated learning in higher education, but its effectiveness depends on careful pedagogical design and thoughtful integration into existing teaching practices. The challenge for higher education institutions is not whether artificial intelligence should be used in formative assessment, but how it can be employed in ways that strengthen student autonomy, preserve critical reflection, and cultivate the capacities required for lifelong learning in increasingly digital educational environments.

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