

Designing generative AI-powered reflective learning dashboards for enhancing self-regulated learning in higher education

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A reflective learning dashboard powered by generative artificial intelligence (AI) was developed to enhance self-regulated learning, student engagement, academic performance and learner perceptions in higher education. Grounded in learning analytics and generative feedback pedagogy, the system integrates behavioural data with AI-generated reflective dialogue to support continuous metacognitive development. Using a quasi-experimental design, 180 undergraduate students participated in a 12-week intervention comparing traditional instructor feedback with AI-generated reflective feedback. Quantitative results revealed significant improvements in self-regulated learning behaviours, time on task, login frequency and academic performance ($p < .001$), indicating strong effects on both cognitive and behavioural dimensions of learning. In addition, students reported high levels of perceived usefulness, trust, personalisation and positive attitudes towards AI-generated feedback, supported by qualitative insights highlighting increased motivation and learner agency. The findings demonstrate that combining generative AI with learning analytics transforms feedback into a dynamic, dialogic process that enhances reflective thinking and adaptive learning. This study contributes a scalable, human-centred and ethically grounded model for improving both learning outcomes and learner experience in digital education environments.

Implications for practice or policy:

- University administrators should implement transparent AI dashboards ensuring ethics, privacy and accountability.
- Educators can enhance reflective learning by integrating adaptive AI feedback that supports metacognitive development.
- Policymakers should promote AI literacy and self-regulated learning within higher education frameworks.
- Technology developers need to design user-centred and interpretable AI systems aligned with pedagogical objectives.
- Higher education leaders should foster AI-supported reflection, professional development and evidence-based innovation for sustainable transformation.

Keywords: generative artificial intelligence, reflective learning dashboard, self-regulated learning, learning analytics, higher education

Introduction

Self-regulated learning (SRL) refers to learners' capacity to set goals, monitor progress and reflect on outcomes to manage their cognitive and emotional engagement. SRL is widely recognised as a critical factor influencing learner engagement, persistence and academic performance in higher education (Butler & Winne, 1995; Zimmerman & Schunk, 2011). Feedback plays a central role in supporting SRL because it helps learners evaluate progress, identify weaknesses and adjust learning strategies throughout the learning process (Mäkipää, 2024). However, traditional classroom environments often struggle to support SRL effectively because feedback is frequently delayed, generic and limited in personalisation, reducing opportunities for continuous reflection and adaptive learning behaviours (Akhasbi et al., 2025; Zhan et al., 2025).

Traditional feedback models often position students as passive recipients of instructor comments, limiting active engagement in reflective learning processes (Zhan et al., 2025). Conventional learning analytics dashboards have improved this situation by visualising performance data and increasing learner awareness of progress, participation and engagement patterns (Banihashem, Bond, et al., 2025). However, many dashboards remain primarily descriptive, focusing on monitoring and reporting rather than supporting interpretive and dialogic reflection. As a result, learners may struggle to translate visual analytics into meaningful actions for improving their learning strategies. Dashboards powered by generative artificial intelligence (AI) extend beyond descriptive analytics by transforming behavioural data into personalised, adaptive and conversational feedback through natural language generation (Wu & Chiu, 2025). Unlike traditional dashboards, generative AI systems can provide reflective prompts, contextual explanations and human-like dialogue that encourage learners to evaluate their progress, adjust strategies and engage more actively in SRL processes. These differences suggest that generative AI dashboards may support SRL more effectively by strengthening reflection, engagement and adaptive learning behaviours.

Despite the growing adoption of generative AI in educational environments, significant ethical concerns remain regarding transparency, fairness, privacy and learner autonomy (Yan et al., 2024). Because generative AI systems often rely on large-scale behavioural data and complex language models, learners may question how their data are collected, interpreted and used to generate feedback. In addition, the opacity of AI-generated responses may reduce trust if feedback is perceived as inaccurate, biased or difficult to explain (Jin, Maheshi, et al., 2025; Lai, 2024). Responsible implementation therefore requires transparent communication, ethical data governance, informed consent and appropriate human oversight to ensure that AI functions as a supportive educational tool rather than an uncontrollable evaluative mechanism. Learners' perceptions of usefulness, trust, personalisation and motivation therefore become important factors in evaluating AI-generated reflective feedback systems (Yi et al., 2025).

Growing interest in learning analytics and AI in higher education has encouraged researchers to explore new approPs for supporting student learning (Jin, Yang, et al., 2025; Paulsen & Lindsay, 2024; Rodríguez-Ortiz et al., 2025). However, studies have often examined learning analytics dashboards and AI-generated feedback as separate educational approaches. Most conventional dashboard research has focused primarily on visualisation, monitoring and descriptive reporting (Masiello et al., 2024; Villagrán et al., 2024), while studies on generative AI have emphasised automation and conversational feedback without fully integrating reflective learning analytics to support continuous SRL processes (Awidi, 2024; Kong & Yang, 2024; Yan et al., (2024). In addition, limited research has simultaneously examined the effects of generative AI-powered dashboards on SRL, learner engagement, academic performance and learner perceptions within authentic higher education environments (Banihashem, Bond, et al., 2025; Lan & Zhou, 2025). To address these gaps, this study developed and evaluated a generative AI-powered reflective learning dashboard (GAI-RLD) designed to support reflective learning through adaptive AI-generated feedback based on student behavioural data (Salinas-Navarro et al., 2024a; Wu & Chiu, 2025). The study specifically investigated how GAI-RLD influences SRL, engagement, academic performance and learner perceptions in higher education settings.

The research questions (RQs) were:

1. How does GAI-RLD influence students' SRL (planning, monitoring and reflection) compared with traditional instructor feedback?
2. How does GAI-RLD affect student engagement (time on task, login frequency, participation) and academic performance (final grades)?
3. What are students' perceptions of AI-generated reflective feedback in terms of usefulness, trust, personalisation and motivation?
4. To what extent does SRL mediate the relationship between GAI-RLD use and academic performance?

To ensure conceptual consistency, all variables examined in this study were explicitly aligned with the RQs, data collection instruments, data collection procedures, statistical analyses and reported findings throughout the manuscript.

Literature review

Importance of SRL in online learning

SRL plays an important role in online learning because learners must independently manage goals, monitor progress, regulate motivation and adapt learning strategies with limited direct instructor supervision (Lämsä et al., 2025; Nasrullah et al., 2024; Nguyen & Nguyen, 2024). In digital learning environments, SRL supports learner engagement, persistence and academic achievement through planning, monitoring and reflective learning behaviours (Sardi et al., 2025). However, online learning environments often lack sufficient scaffolds to support continuous self-monitoring and reflection. Feedback is frequently delayed, summative and insufficiently personalised, limiting students' ability to interpret their learning progress and adjust strategies effectively. Research in educational technology therefore has emphasised the importance of metacognitive scaffolds and timely feedback mechanisms that encourage learners to plan, monitor and reflect on their learning processes (Khalil et al., 2024). Within this context, learning analytics dashboards have emerged as important tools for supporting SRL in online education (Karlen & Hertel, 2024).

Role of feedback as a foundation for improving SRL

Learning analytics dashboards transform student activity data into visual insights that reveal engagement, progress and performance patterns (Alcock et al., 2024; Masiello et al., 2024; Villagrán et al., 2024). However, many dashboards remain descriptive, showing past performance without guiding improvement, which can limit learners' ability to regulate their own learning processes and make meaningful behavioural adjustments (Paulsen & Lindsay, 2024). To address this limitation, recent educational technology research has emphasised the importance of interactive and dialogic feedback within dashboard environments (Kitto et al., 2025). Integrating reflective prompts and adaptive narratives helps learners interpret feedback, evaluate progress and plan subsequent learning strategies. Such feedback mechanisms strengthen SRL by supporting planning, monitoring and reflection processes. Generative AI further extends this capability by delivering personalised and contextual feedback, transforming dashboards from passive monitoring tools into intelligent systems that actively support reflective learning and metacognitive development.

Evolution of feedback in online learning (dashboards with and without generative AI)

The evolution of feedback in online learning has progressed from traditional instructor-centred feedback towards data-driven and AI-supported learning environments. Early learning analytics dashboards primarily focused on visualising learner engagement, participation and performance data to support monitoring and self-awareness (Masiello et al., 2024; Villagrán et al., 2024). Although these dashboards improved access to learning information, many remained descriptive and static, requiring learners to independently interpret data and determine appropriate learning adjustments (Paulsen & Lindsay, 2024). To address these limitations, recent approaches have integrated dialogic and adaptive feedback mechanisms within dashboard systems (Kitto et al., 2025). Generative AI further extends this evolution by enabling dashboards to produce personalised, contextual and conversational feedback through models such as GPT and PaLM (Awidi, 2024; Zhan & Yan, 2025). In higher education, these systems support reflection, self-regulation and critical thinking by transforming dashboards from passive monitoring tools into interactive reflective learning environments (Kong & Yang, 2024; Salinas-Navarro et al., 2024b). The GAI-RLD applies this approach by translating learning analytics into adaptive reflective prompts that encourage insight, goal adjustment and metacognitive development (Huesca et al., 2025).

Zimmerman's SRL framework as the theoretical foundation for a GAI-RLD

Zimmerman and Schunk's (2011) SRL framework provides an important theoretical foundation for understanding how learners actively manage and improve their learning processes through cyclical phases of planning, monitoring and reflection. In the planning phase, learners establish goals, select strategies and organise learning activities. During the monitoring phase, learners observe their progress, evaluate performance and regulate cognitive and motivational processes. The reflection phase involves evaluating outcomes, identifying strengths and weaknesses and adjusting strategies for future learning. This cyclical process highlights the importance of continuous feedback in supporting adaptive learning behaviours and metacognitive development (Yi et al., 2025). Within this framework, GAI-RLDs function as metacognitive scaffolds by transforming learning analytics into personalised reflective prompts that support each stage of SRL. Through adaptive and dialogic feedback, the GAI-RLD encourages learners to interpret performance data, refine strategies and sustain reflective learning processes in online education environments (Akinyi et al., 2024; Dang et al., 2024; Mislevy, 2024; Pacheco et al., 2025).

Challenges and ethical concerns in using GAI-RLDs

The integration of generative AI into reflective learning dashboards presents significant ethical and pedagogical challenges beyond technical implementation (Khosravi et al., 2025). Although generative AI improves personalisation, immediacy and adaptive feedback, concerns remain regarding privacy, fairness, transparency and learner autonomy. Learners may question how behavioural data are collected, interpreted and used to generate reflective feedback, particularly because the opacity of large language models can make AI-generated responses difficult to explain and evaluate (Xing et al., 2025). Such limitations may reduce trust and acceptance of AI-supported reflective learning systems.

Addressing these concerns requires a human–AI collaboration framework grounded in accountability, informed consent and ethical data governance. Ethical implementation includes transparent communication regarding data use, opportunities for learner control and opt-out participation and appropriate human oversight in interpretation and evaluation processes (Liu et al., 2025). The GAI-RLD adopts these principles to promote fairness, explainability and learner agency within reflective learning environments (Rodríguez-Ortiz et al., 2025). By emphasising transparency and responsible AI integration, the system aims to strengthen trust while supporting effective and ethical AI-enhanced feedback in higher education.

Conceptual gap addressed by the present study

Although studies have demonstrated the effectiveness of learning analytics dashboards and AI-driven feedback in online learning environments, these approaches have often been examined independently rather than as integrated reflective learning systems. Dashboard research has primarily emphasised visualisation, monitoring and self-tracking functions, while studies on generative AI feedback have frequently focused on automation, personalisation and instructional efficiency (Banihashem, Norrozi, et al., 2025). Limited research has explored how generative AI can be integrated with learning analytics to support continuous SRL through adaptive reflective dialogue in authentic higher education settings.

The present study addressed this conceptual gap by developing and evaluating a GAI-RLD that combines learning analytics, dialogic feedback and SRL theory within a unified reflective learning framework. The study contributes to literature by examining how AI-generated reflective feedback influences SRL, learner engagement, academic performance and learner perceptions in higher education. In addition, the GAI-RLD framework provides a scalable and ethically grounded approach for integrating generative AI into reflective learning environments, supporting metacognitive development and lifelong learning competencies (Cosentino et al., 2025).

Research design and methodology

Research design overview

This study employed a mixed methods quasi-experimental design to evaluate the effectiveness of the GAI-RLD in enhancing SRL, learner engagement, academic performance and learner perceptions in higher education. A quasi-experimental approach was selected because intact classroom groups were assigned to control and experimental conditions within an authentic educational setting. The study was conducted over 12 weeks, comparing traditional instructor feedback with ai-generated reflective feedback. Quantitative data included pre-test and post-test measures, learning management system (LMS) behavioural analytics and academic performance indicators, while qualitative data from semi-structured interviews provided deeper insights into learners' reflective experiences and perceptions of AI-supported feedback.

Participants and context

Participants consisted of 180 undergraduate students enrolled in digital innovation and educational technology courses at Chiang Mai University, Thailand. The study employed class-level purposive sampling within authentic classroom settings, with intact classes assigned to either the control or experimental condition to minimise contamination between groups. One class ($n = 90$) received traditional instructor feedback, while another class ($n = 90$) interacted with the GAI-RLD. Participants were between 20 and 22 years old ($M = 21.0$, $SD = 1.2$) with experience using digital learning platforms. Ethical approval was granted by the university's Institutional Review Board, and written informed consent was obtained from all participants in accordance with Thailand's *Personal Data Protection Act. B.E. 2562* (Royal Thai Government, 2019).

GAI-RLD design and features

The GAI-RLD was designed as an intelligent feedback system integrating learning analytics, generative AI and reflective pedagogy to support SRL. The system consists of four interconnected components. First, the data ingestion layer collects LMS behavioural data, including login frequency, time on task, task completion and discussion participation. Second, the analytics engine identifies engagement patterns and performance trends to support adaptive feedback generation. Third, the generative AI feedback module uses a fine-tuned language model to generate personalised reflective prompts that encourage planning, monitoring, and reflection. Finally, the visualisation and interface layer presents learner progress, comparative analytics and reflection histories through interactive dashboards that support both student self-monitoring and instructor oversight.

Course description and implementation

The study was implemented within undergraduate digital innovation and educational technology courses at Chiang Mai University, Thailand. The courses were delivered through a blended online learning environment supported by the university's LMS. Students participated in weekly online learning activities, including discussions, assignments, quizzes and reflective learning tasks throughout the 12-week intervention period. Both the control and experimental groups received identical instructional content, learning objectives and assessment activities to ensure instructional consistency. The control group received traditional instructor feedback through the LMS, while the experimental group used the GAI-RLD, which provided adaptive reflective prompts and personalised AI-generated feedback based on learners' behavioural data and engagement patterns. Figures 1–4 illustrate the overall system architecture, dashboard interface, AI-generated reflective feedback interface and learning analytics visualisation module used throughout the course implementation.

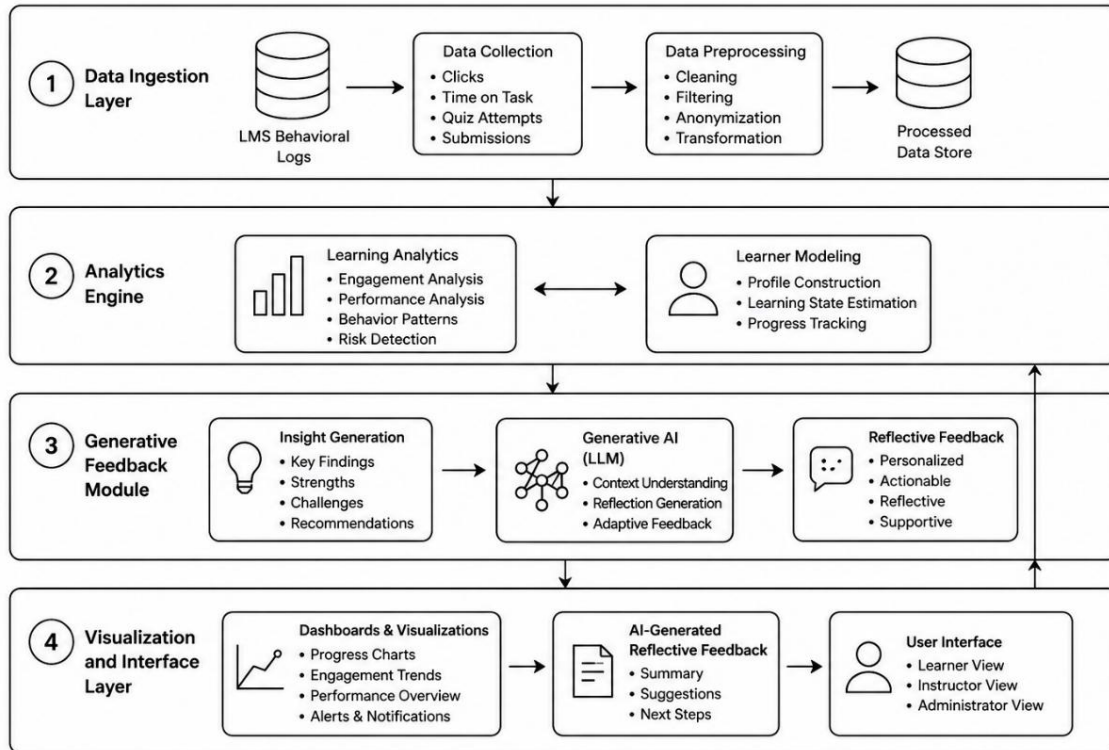


Figure 1. Overall system architecture of GAI-RLD

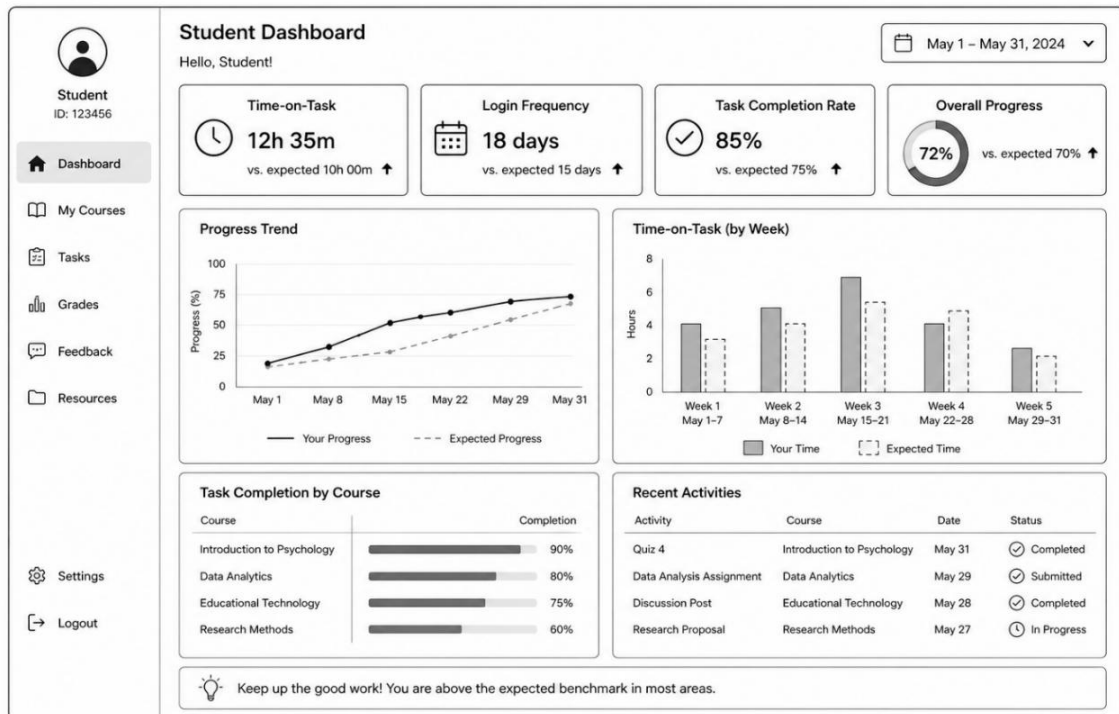


Figure 2. Main dashboard interface for student learning analytics

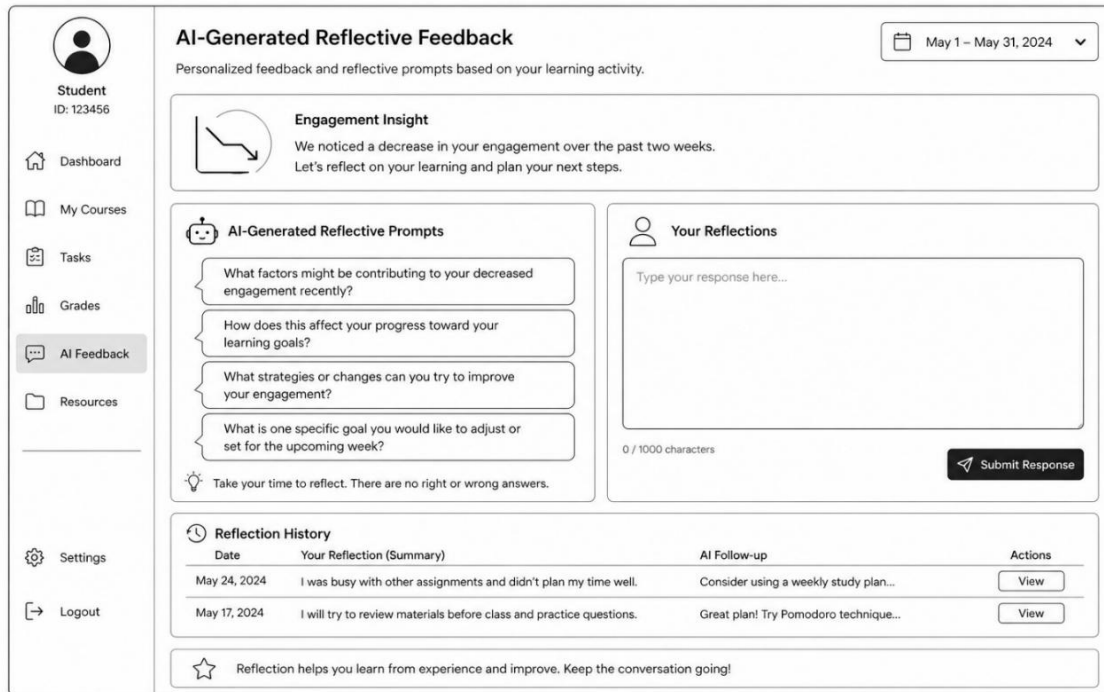


Figure 3. AI-generated reflective feedback interface

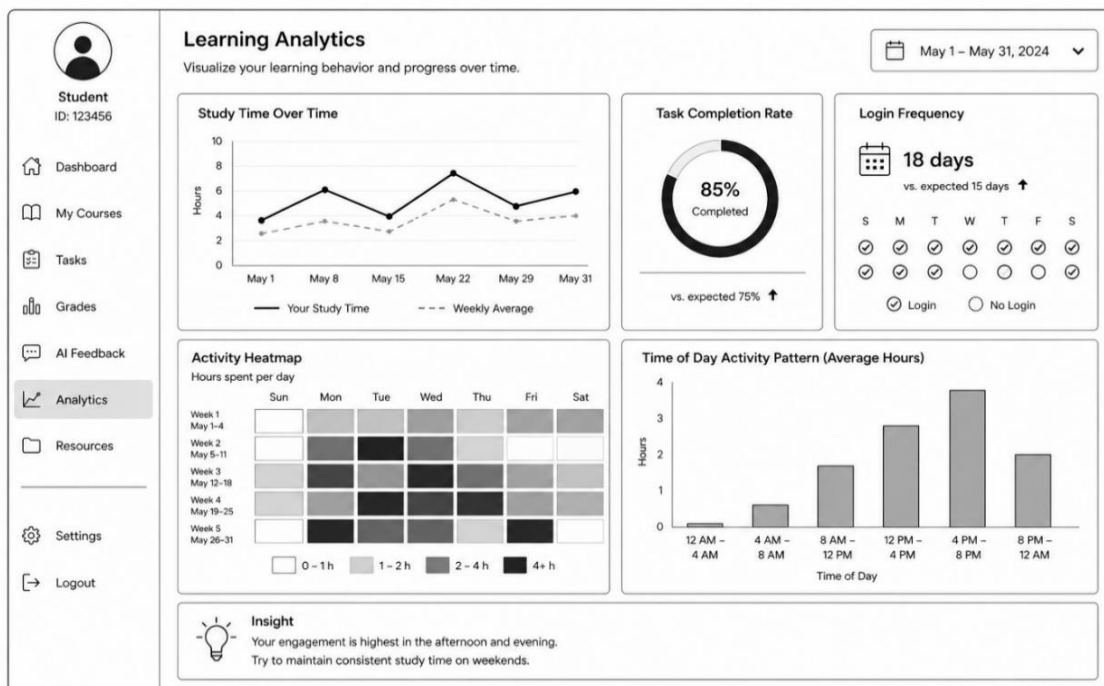


Figure 4. Learning analytics visualisation module

Data collection instruments

The study employed multiple instruments directly aligned with the RQs and study variables. SRL, serving as both a dependent and mediating variable, was measured using the Self-Regulated Learning Scale, adapted from the Motivated Strategies For Learning Questionnaire (Antwi et al., 2026), consisting of 24 closed-ended Likert-scale items assessing planning, monitoring and reflection. Student engagement was measured through objective LMS behavioural metrics, including time on task, login frequency and

participation. Academic performance was measured using final course grades. Learner perceptions were measured using the Reflective Feedback Perception Survey (RFPS; Nakata et al., 2025), consisting of 18 closed-ended Likert-scale items evaluating usefulness, trust, personalisation and motivation towards AI-generated reflective feedback. In addition, open-ended semi-structured interview questions were used with experimental group participants to explore reflective experiences with and perceptions of the GAI-RLD.

Implementation of intervention and data collection

The intervention and data collection procedures were organised into three phases to improve methodological clarity and alignment with the RQs. During the pre-intervention phase (Week 1), baseline data were collected, including gender, age, academic major, prior AI familiarity, LMS familiarity and SRL scores. Prior AI familiarity referred to students' previous experience using generative AI tools such as ChatGPT or AI-assisted learning applications, measured using a 5-point self-report familiarity scale. LMS familiarity referred to students' prior experience using the university's LMS for online learning activities, also measured using a 5-point self-report scale. Baseline engagement and academic performance indicators were derived from students' prior LMS activity records and previous course assessment data to establish pre-intervention equivalence between groups.

During the intervention phase (Weeks 2–11), both groups participated in the same instructional activities and course content within the LMS environment. The control group received traditional instructor feedback, while the experimental group interacted with the GAI-RLD, receiving adaptive AI-generated reflective prompts based on behavioural learning data. The implementation process consisted of orientation activities, system familiarisation, reflective learning tasks and continuous engagement monitoring throughout the intervention period.

During the post-intervention phase (Week 12), post-test SRL data, learner perceptions (RFPS), engagement metrics and academic performance outcomes were collected. Engagement variables included time on task, login frequency and participation. Participation was operationalised as the frequency of student involvement in LMS discussion forums, assignment submissions, reflective activities, and collaborative online learning interactions recorded within the system logs. Qualitative interview data were also collected from experimental group participants to provide deeper insights into reflective learning experiences and perceptions of AI-generated feedback.

Data analysis procedures

The data analysis procedures were organised according to the RQs to ensure conceptual consistency between the variables, instruments and statistical analyses. Baseline equivalence analyses were first conducted using chi-square tests of independence for gender and academic major and independent *t* tests for age, prior AI familiarity, LMS familiarity, pre-intervention SRL, engagement and academic performance. Baseline engagement and academic performance indicators were derived from students' previous LMS activity records and prior course assessment results to establish group equivalence before the intervention.

Reliability and validity analyses were then conducted for the SRL Scale and the RFPS. Internal consistency was evaluated using Cronbach's alpha and McDonald's omega coefficients, while confirmatory factor analysis (CFA) was performed to examine construct validity.

For RQ1, independent *t* tests were used to examine post-test differences in overall SRL between the control and experimental groups. In addition, paired *t* tests were conducted separately for the SRL dimensions of planning, monitoring and reflection to examine within-group changes across specific SRL components before and after the intervention.

For RQ2, independent *t* tests were conducted to examine between-group differences in student engagement variables, consisting of time on task, login frequency, participation and academic

performance outcomes. Participation was operationalised as student involvement in LMS discussion forums, assignment submissions, reflective activities and collaborative online interactions.

For RQ3, descriptive statistics, including means and standard deviations, were calculated for the RFPS to examine learner perceptions regarding usefulness, trust, personalisation and motivation. Qualitative interview data were analysed using thematic coding to further explore students' reflective experiences and perceptions of AI-generated feedback.

For RQ4, mediation analysis was conducted to examine whether post-intervention SRL mediated the relationship between instructional condition (GAI-RLD vs control) and academic performance. All quantitative analyses were conducted using SPSS (version 29) with statistical significance set at $p < .05$.

Validity and reliability

Methodological rigour was ensured through multiple strategies. Reliability was confirmed ($\alpha > .85$) and CFA supported construct validity. Procedural and ecological validity were maintained through standardised implementation in authentic settings. Qualitative rigour included member checking, peer debriefing, audit trails and detailed contextual descriptions, ensuring credibility, dependability and transferability of findings.

Ethical considerations

Ethical design was integral to both the research process and system architecture. Data collection complied with Chiang Mai University's human research ethics committee protocols and Thailand's *Personal Data Protection Act. B.E. 2562* (Royal Thai Government, 2019). The GAI-RLD anonymised all personal identifiers before analysis, and participants could delete their reflection records upon request. Transparency statements within the dashboard clarified that feedback was AI generated and non-evaluative.

Results and findings

Reliability and validity of instruments

Before addressing the RQs, baseline equivalence, reliability and validity analyses were conducted to ensure the quality and consistency of the measurement instruments and qualitative coding procedures. Table 1 presents participant demographics and baseline equivalence analyses between the control and experimental groups. Chi-square tests of independence showed no significant differences in gender distribution or academic major between groups ($p > .05$). Independent t tests also indicated no significant differences in age, prior AI familiarity, LMS familiarity, pre-intervention SRL, engagement indicators or baseline academic performance ($p > .05$). Pre-intervention SRL was included to confirm that both groups demonstrated comparable levels of SRL before the intervention. In addition, baseline engagement and academic performance measures were derived from students' prior LMS activity records and previous course assessment results to establish pre-intervention equivalence between groups.

Table 2 presents the psychometric properties of the Self-Regulated Learning Scale and the RFPS. All SRL and RFPS subscales demonstrated strong internal consistency, with Cronbach's alpha and McDonald's omega coefficients exceeding .85. CFA further supported construct validity, with acceptable factor loadings, average variance extracted, composite reliability and strong model fit indices (comparative fit index [CFI] $> .95$; root-mean-square error of approximation [RMSEA] $< .05$). For qualitative analysis, two independent coders analysed the interview transcripts and achieved high inter-coder reliability (Cohen's $\kappa = 0.89$), supporting the credibility and consistency of the thematic findings.

Table 1

Participant profile and baseline equivalence (N = 180)

Variable	Control (n = 90)	Experimental (n = 90)	Total	χ^2 / t	p
Gender (M & F)	48 & 42	46 & 44	94 & 86	$\chi^2(1) = 0.09$	.764
Age (years), $M \pm SD$	20.90 $\pm$ 1.10	21.10 $\pm$ 1.20	21.00 $\pm$ 1.20	$t(178) = 1.16$	.248
Major: business technology	35 (38.90%)	32 (35.60%)	67 (37.20%)	$\chi^2(2) = 0.36$	.835
Major: information systems	28 (31.10%)	30 (33.30%)	58 (32.20%)		
Major: design innovation	27 (30.00%)	28 (31.10%)	55 (30.60%)		
Prior AI tool experience (%)	33.30	36.70	35.00	$t(178) = 1.10$	.274
LMS familiarity (1–5)	3.92 $\pm$ 0.61	3.95 $\pm$ 0.58	3.94 $\pm$ 0.59	$t(178) = 0.34$	.735

Note. Baseline balance was satisfactory; no significant differences at pre-test.

Table 2

Instrument reliability and construct validity

Instrument & subscale	k	α	ω	Example item	CFA λ (range)	AVE	CR	Model fit (CFA)
SRL, planning	8	0.88	.89	"I set specific goals"	0.62–0.81	0.57	0.90	$\chi^2/df = 2.11$ CFI = 0.95 TLI = 0.94 RMSEA = 0.046
SRL, monitoring	8	0.90	0.91	"I track how well"	0.64–0.85	0.60	0.91	
SRL, reflection	8	0.91	0.92	"I evaluate my learning"	.66–.86	0.62	0.92	
RFPS, usefulness	6	0.87	0.88	"The AI feedback was useful."	0.63–0.83	0.56	0.89	$\chi^2/df = 2.24$ CFI = 0.96 TLI = 0.95 RMSEA = 0.049
RFPS, rust	6	0.86	0.87	"I trusted the AI messages."	0.61–0.82	0.55	0.88	
RFPS, personalisation	6	0.88	0.89	"Feedback felt tailored to me."	0.65–0.84	0.59	0.90	

Note. AVE = average variance extracted. CR = composite reliability. TLI = Tucker-Lewis index. α = Cronbach's alpha; ω = McDonald's omega.

Effects on SRL (RQ1)

Table 3 further reinforces experimental validity by confirming no significant pre-test differences between groups in SRL, engagement or academic performance ($p > .50$). This ensures both groups started at comparable cognitive and motivational levels, allowing post-intervention changes to be confidently attributed to the dashboard intervention. Table 4 highlights strong post-test effects. The experimental group showed a substantial increase in SRL scores, rising from 3.12 to 3.68 ($\Delta = +0.56$), representing a large effect size (Cohen's $d = 1.07$, $p < .001$). Engagement indicators such as time on task and login frequency also increased significantly ($d > 1.5$), demonstrating improved behavioural participation. Academic performance improved by an average of 7.6 points. Additionally, the RFPS usefulness rating was

significantly higher in the experimental group (4.28 vs 3.42), indicating that students perceived AI-generated feedback as more effective and personalised. Table 5 presents within-group comparisons across the SRL dimensions of planning, monitoring and reflection. While the independent *t* test in Table 4 examined overall post-intervention SRL differences between the control and experimental groups, the paired *t* tests in Table 5 were conducted separately for SRL dimensions to provide a more detailed analysis of changes within specific metacognitive components of Zimmerman and Schunk's (2011) cyclical SRL framework. The experimental group demonstrated significant improvements across planning (+0.60), monitoring (+0.54) and reflection (+0.54), all statistically significant ($p < .001$), whereas the control group showed only minor gains. Large within-group effect sizes ($dz > 1.1$) further indicate substantial metacognitive development associated with the GAI-RLD intervention.

Table 3

Pre-test equivalence on key outcomes

Measure (pre-test)	Scale	Control <i>M</i> ± <i>SD</i>	Experimental <i>M</i> ± <i>SD</i>	<i>t</i> (178)	<i>p</i>	Cohen's <i>d</i>
SRL total	1–5	3.08 ± 0.42	3.12 ± 0.41	0.67	.503	0.10
Time on task (hr/wk)	hrs	6.18 ± 1.43	6.26 ± 1.37	0.40	.692	0.06
Login frequency (per wk)	count	4.77 ± 1.19	4.85 ± 1.21	0.47	.639	0.07
Quiz avg. (%)	0–100	68.90 ± 7.80	69.20 ± 7.50	0.27	.789	0.04

Note. No statistically significant pre-test differences were observed between the control and experimental groups across any baseline measure ($p > .05$), indicating baseline equivalence between groups.

Table 4

Post-test outcomes and between-group differences (Week 12)

Outcome	Control <i>M</i> ± <i>SD</i>	Experimental <i>M</i> ± <i>SD</i>	<i>t</i> (178)	<i>p</i>	Cohen's <i>d</i>	95% CI (<i>d</i>)
SRL total (1–5)	3.21 ± 0.45	3.68 ± 0.44	7.22	<0.001	1.07	[0.76, 1.38]
Time on task (hrs/wk)	6.82 ± 1.51	9.31 ± 1.48	11.29	<0.001	1.68	[1.33, 2.03]
Login frequency (per wk)	5.26 ± 1.28	7.51 ± 1.49	10.09	<0.001	1.50	[1.17, 1.83]
Final grade (%)	74.3 ± 8.1	81.9 ± 7.6	6.49	<0.001	0.97	[0.67, 1.27]
RFPS – usefulness (1–5)	3.42 ± 0.63	4.28 ± 0.58	9.13	<0.001	1.36	[1.04, 1.68]

Note. Bold indicates higher mean. 2-tailed tests; $\alpha = 0.05$.

Table 5

Within-group pre–post changes on SRL subscales

Subscale (1–5)	Group	Pre- <i>M</i> ± <i>SD</i>	Post- <i>M</i> ± <i>SD</i>	Δ	<i>t</i>	<i>p</i>	<i>dz</i>
Planning	Control	3.11 ± 0.47	3.26 ± 0.49	+0.15	3.02	0.003	0.32
	Experimental	3.12 ± 0.46	3.72 ± 0.45	+0.60	12.41	<0.001	1.31
Monitoring	Control	3.03 ± 0.44	3.19 ± 0.46	+0.16	3.28	0.001	0.35
	Experimental	3.10 ± 0.43	3.64 ± 0.44	+0.54	11.26	<0.001	1.19
Reflection	Control	3.09 ± 0.45	3.20 ± 0.47	+0.11	2.12	0.036	0.22
	Experimental	3.14 ± 0.44	3.68 ± 0.47	+0.54	10.73	<0.001	1.13

Note. *dz* = within-group effect size (paired).

Effects on engagement and academic performance (RQ2)

Table 6 presents the independent *t* test results examining differences between the control and experimental groups in engagement variables and academic performance outcomes following the intervention. The experimental group demonstrated significantly higher time on task, login frequency, participation and final academic performance compared with the control group ($p < .001$). Participation was operationalised as the frequency of student involvement in LMS discussion forums, assignment submissions, reflective learning activities and collaborative online interactions recorded within the system

logs. Large effect sizes across engagement indicators suggest that the GAI-RLD intervention substantially improved both behavioural engagement and academic achievement.

Engagement variables were analysed separately rather than combined into a composite engagement score because each indicator represented distinct dimensions of learner behaviour within the LMS environment. Time on task reflected sustained learning effort, login frequency represented system access and interaction regularity and participation measured active involvement in reflective and collaborative learning activities. Analysing these variables independently allowed a more precise interpretation of how the GAI-RLD influenced different aspects of learner engagement.

Table 6

Post-intervention engagement and academic performance differences (RQ2)

Outcome	Control <i>M ± SD</i>	Experimental <i>M ± SD</i>	<i>t</i> (178)	<i>p</i>	Cohen's <i>d</i>
Time on task (hr/wk)	6.82 ± 1.51	9.31 ± 1.48	11.29	< .001	1.68
Login frequency (per wk)	5.26 ± 1.28	7.51 ± 1.49	10.09	< .001	1.5
Participation score	3.84 ± 0.71	4.69 ± 0.66	8.23	< .001	1.23
Final grade (%)	74.3 ± 8.1	81.9 ± 7.6	6.49	< .001	0.97

Mediation role of SRL between GAI-RLD and academic performance (RQ4)

Table 7 presents the mediation analysis examining whether post-intervention SRL mediated the relationship between instructional condition (GAI-RLD vs control) and academic performance. The results showed that the pathway from instructional condition to SRL improvement was statistically significant ($a = 0.47, p < .001$), indicating that students using the GAI-RLD demonstrated substantially greater SRL gains than those receiving traditional instructor feedback. In addition, the pathway from SRL improvement to final academic performance was also significant ($b = 8.21, p < .001$), demonstrating that increased SRL was strongly associated with improved academic outcomes.

The indirect effect of GAI-RLD on academic performance through SRL was statistically significant ($a \times b = 3.86, 95\% \text{ CI } [2.09, 6.20]$), confirming partial mediation. Approximately 53% of the total effect of GAI-RLD on final academic performance was explained through improvements in SRL. Although the direct effect of instructional condition on academic performance remained significant after controlling for SRL ($c' = 3.43, p = .004$), the mediation results indicate that SRL functioned as a major explanatory mechanism linking AI-generated reflective feedback with improved learning outcomes.

Table 7

Mediation of GAI-RLD effect on final grade via SRL gain

Path	Coefficient (<i>B</i>)	<i>SE</i>	95% CI	<i>p</i>
a: Group → SRL gain	0.47	0.06	[0.36, 0.59]	<0 .001
b: SRL gain → Final grade	8.21	1.92	[4.45, 12.03]	<0 .001
c: Total effect (group → grade)	7.28	1.12	[5.07, 9.49]	<0 .001
c': Direct effect (controlling SRL gain)	3.43	1.18	[1.10, 5.74]	0.004
Indirect effect ($a \times b$)	3.86	1.01	[2.09, 6.20]	Bootstrapped (5,000)

Note. Partial mediation: approx. 53% of GAI-RLD's effect on grade is via SRL improvement.

Learner perceptions and attitudes towards GAI-RLD (RQ3)

Table 8 presents descriptive statistics from the RFPS, examining students' perceptions of AI-generated reflective feedback in terms of usefulness, trust, personalisation and motivation. The experimental group reported high levels across all dimensions, indicating positive attitudes towards the GAI-RLD system. Perceived usefulness received the highest rating, followed by personalisation and motivation, suggesting that students valued the adaptive and reflective nature of the AI-generated feedback. Trust also

demonstrated a high mean score, indicating acceptance of AI-supported reflective learning within the online learning environment.

Table 8
RFPS results (RQ3)

RFPS dimension	M	SD	Interpretation
Usefulness	4.28	0.58	Very high
Trust	4.11	0.61	High
Personalisation	4.24	0.56	Very high
Motivation	4.19	0.6	High
Overall RFPS	4.21	0.59	High

Note. RFPS scores were measured on a 5-point Likert scale (1 = *strongly disagree*; 5 = *strongly agree*).

Qualitative interview data from 20 experimental group participants were analysed using thematic coding. Several themes emerged from the interviews, consisting of feedback as dialogue, pedagogical adaptivity, trust and transparency, and motivation and agency. These qualitative findings further support the RFPS results by demonstrating that students perceived the GAI-RLD system as an interactive, reflective and supportive learning partner rather than a passive monitoring tool.

Analytics operationalisation for reproducibility

Table 9 presents seven weekly behavioural metrics supporting GAI-RLD's analytics framework: reflection frequency, AI response rate, interaction depth, goal updates, peer discussion, late-night study ratio and alert resolutions. Results show strong engagement (2.6 reflections per week; 76.4% response rate) and meaningful dialogue (3.1 interactions/session). Goal updates and peer discussions reflect active self-regulation and collaboration, while well-being indicators extend analysis beyond academics.

Table 9
Dashboard interaction metrics (Weeks 2–11, experimental group n = 90)

Metric	$M \pm SD$	Md	Min. to max.	Interpretation threshold
Reflection frequency (entries/wk)	2.60 ± 0.90	2.00	1–5	≥ 2.0 indicates sustained reflection
AI prompt response rate (%)	76.4 ± 12.10	78.00	44–96	$\geq 70\%$ indicates high engagement
Interaction depth (messages/session)	3.10 ± 1.00	3.00	1–6	≥ 3 shows dialogic exchange
Goal updates (per wk)	1.40 ± 0.60	1.00	0–3	≥ 1 indicates active planning
Peer discussion posts (per wk)	3.30 ± 1.70	3.00	0–8	≥ 3 linked to higher grades
Late-night study ratio (%)	24.70 ± 9.80	23.00	8–49	$> 40\%$ flags fatigue risk
Alert resolutions (per wk)	1.10 ± 0.70	1.00	0–3	≥ 1 shows prompt follow-through

Note. Metrics in Table 9 were derived from LMS logs and dashboard interaction records. Higher values generally indicate greater learner engagement, self-regulation and interaction with the GAI-RLD system.

Integrative interpretation

Synthesising quantitative, qualitative and analytic evidence, the findings confirm GAI-RLD as an effective catalyst for metacognitive development in digital learning. Generative reflection transformed learners from passive recipients into active interpreters of their learning data, resulting in significant improvements in SRL, engagement and performance. Regression and mediation analyses showed that SRL growth was the key mechanism driving these gains, while qualitative insights revealed increased trust, autonomy and reflective awareness.

Discussion

The findings of this study demonstrate that the GAI-RLD significantly improved SRL learner engagement, academic performance and learner perceptions in higher education. These findings are consistent with studies emphasising the importance of SRL in online learning environments, where learners are required to independently manage goals, monitor progress and regulate learning behaviours (Lämsä et al., 2025; Nasrullah et al., 2024). The significant improvements observed in planning, monitoring and reflection support Zimmerman and Schunk's (2011) cyclical SRL framework and reinforce research showing that timely and adaptive feedback strengthens metacognitive development (Yi et al., 2025). Unlike traditional instructor feedback and conventional dashboards that mainly provide descriptive information, the GAI-RLD transformed learning analytics into personalised reflective dialogue, supporting the argument that generative AI can function as an active metacognitive scaffold (Kong & Yang, 2024; Wu & Chiu, 2025).

The results related to engagement and academic performance further support previous literature on learning analytics dashboards and AI-supported feedback systems. Consistent with Villagrán et al. (2024) and Kitto et al. (2025), the findings indicate that interactive and dialogic feedback can increase learner participation and sustained engagement in online learning environments. The higher time on task, login frequency and participation scores observed in the experimental group suggest that generative AI feedback encourages more active involvement in learning activities. In addition, the mediation analysis demonstrate that improvements in SRL partially explain the positive effect of GAI-RLD on academic performance, reinforcing earlier studies suggesting that SRL functions as a critical mechanism connecting reflective learning processes with academic success (Banihashem, Noroozi, et al., 2025; Xu et al., 2025).

Learner perception findings also align with studies emphasising the importance of trust, personalisation and transparency in AI-supported educational systems (Jin et al., 2025; Liu et al., 2025). Students reported high levels of usefulness, motivation and personalisation towards AI-generated reflective feedback, while qualitative findings indicated that learners perceived the system as a supportive reflective partner rather than a passive monitoring tool. These findings support previous arguments that dialogic and adaptive feedback strengthens learner agency and reflective awareness in digital learning environments (Zhan et al., 2025). Furthermore, the positive perceptions regarding trust and transparency suggest that the ethical design principles integrated into the GAI-RLD framework help address the concerns related to privacy, explainability and learner autonomy identified in earlier generative AI research (Khosravi et al., 2025; Rodríguez-Ortiz et al., 2025).

Overall, the findings extend research by demonstrating how generative AI, learning analytics and SRL theory can be integrated within a unified reflective learning system in authentic higher education settings. The study therefore contributes empirical evidence supporting the educational value of generative AI-powered dashboards as scalable and human-centred tools for enhancing reflective learning, metacognitive development and academic performance in digital education environments.

Conclusion

This study examined the effectiveness of a GAI-RLD in enhancing SRL, learner engagement, academic performance and learner perceptions in higher education. The findings demonstrated that students using the GAI-RLD showed significantly higher levels of planning, monitoring, reflection, engagement and academic performance compared with students receiving traditional instructor feedback. In addition, learners reported positive perceptions regarding usefulness, trust, personalisation and motivation towards AI-generated reflective feedback. The mediation analysis further revealed that improvements in SRL partially explained the positive relationship between GAI-RLD use and academic performance, reinforcing the importance of reflective learning processes in digital education environments.

The study contributes theoretically by integrating SRL theory, learning analytics and generative AI within a unified reflective learning framework. Practically, the findings suggest that generative AI-powered

dashboards can function as scalable and human-centred tools for supporting adaptive feedback, reflective learning and metacognitive development in higher education.

Several limitations should be acknowledged. The quasi-experimental design and single institutional context may limit generalisability, while the study primarily relied on behavioural learning analytics data. Future research should therefore examine longitudinal and multi-institutional implementations, integrate multimodal learning analytics and explore affective learning dimensions such as motivation, confidence and learner well-being to further evaluate the long-term impact of AI-supported reflective learning systems.

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