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Delegators or Self-regulators?
Exploring University Students' Self-Regulated Learning with AI[1]

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Introduction

The integration of Artificial Intelligence (AI), particularly generative AI (GenAI), has created both opportunities and challenges in Higher Education. These technologies can provide students with immediate access to explanations, personalised feedback, and problem-solving strategies that can complement traditional learning resources (Chang & Sun, 2024). A recent systematic review confirms that AI is being adopted across multiple domains, such as academic writing, assessment support, and personalised tutoring, while simultaneously raising concerns about academic integrity, ethical use, and potential decline of student autonomy (Qian, 2025). However, AI use comes with significant risks: over-reliance on AI may damage critical thinking, reduce student agency, and impair the development of essential metacognitive and self-regulatory skills (Lan & Zhou, 2025). Such risks are often associated with the phenomenon of cognitive offloading when students rely on external tools like AI to manage cognitive effort.

These findings have prompted calls for pedagogical "guardrails" that ensure AI integration promotes, rather than replaces, active learning strategies (Banihashem et al., 2025). So, the fundamental question is whether AI functions as a scaffold for self-directed learning or as a shortcut that undermines educational effort, a distinction that depends largely on how students engage with these technologies. Although some studies have investigated how students perceive AI tools, there is still limited empirical data on how students actually use them. Specifically, we know little about how often students rely on AI, at what points during the learning process they seek its help, and whether these behaviours reflect effective self-regulation. Recent experimental research indicates that students often engage with AI early in their learning process but tend to postpone more meaningful interactions until later stages (Chen et al., 2025). These usage patterns mirror broader trends observed in digital learning environments, where learners frequently delay seeking help or use support tools in a suboptimal way (Gillies & Turner, 2025). Some other evidence suggests that students with performance-oriented goals, focused on getting good grades, tend to use AI more as a quick tool to complete tasks; in contrast, students with mastery-oriented goals, focused on truly understanding the material, are more likely to engage with AI thoughtfully and use it to improve their learning (Sung & Thomas, 2025).

It also remains unclear whether distinct student profiles emerge in AI-supported contexts based on self-regulatory approaches. Prior research has identified distinct types of self-regulated learners in digital learning, such as delegators, regulators, and procrastinators, using latent class analysis (Barnard-Brak et al., 2010; Koivuniemi et al., 2018). Recent reviews confirm that Zimmerman's

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model dominates AI and Self-Regulated Learning (SRL) literature but point to under-explored motivational and contextual regulation components (Banihashem et al., 2025).

This study tries to address these gaps by focusing on university students' use of AI in relation to SRL, in particular investigating whether there are distinct profiles of students based on their SRL strategies with AI and whether this depends on how often (frequency) and when (timing) students use AI.

Theoretical background

1.1 Self-Regulated Learning

SRL is defined as «an active, constructive process whereby learners set goals for their learning and then attempt to monitor, regulate, and control their cognition, motivation, and behaviour, guided and constrained by their goals and the contextual features in the environment» (Pintrich, 2000, p. 453). Different frameworks shape the SRL literature, i.e., those developed by Zimmerman, Winne and Hadwin, Boekaerts, and Pintrich. A comparative review confirms the ongoing relevance of the different models and highlights their compatibility in explaining how learners plan, execute, and adapt their learning processes (Panadero, 2017). In this paper, we draw primarily on Pintrich's model (2000, 2004), which conceptualises SRL as an active and constructive process consisting of four phases: forethought, planning, and activation, monitoring, control, and reflection/reaction. Each phase can be applied to multiple areas of regulation (cognitive, motivational, behavioural, and contextual); our analysis focuses specifically on cognitive regulation. We also take into account Zimmerman's triadic model (2011), which distinguishes three cyclical self-regulatory phases: forethought, performance, and self-reflection.

Despite its proven link to academic success across domains and levels (Zheng & Sun, 2024), SRL remains a cognitively demanding process that not all learners perform effectively on their own. In recent years, researchers have increasingly focused on the role of cognitive offloading technological tools that support SRL by reducing cognitive load and externalising regulatory processes. These include learning dashboards, digital journal writing, and adaptive feedback systems. Writing-to-learn approaches, for instance, have been shown to scaffold SRL by offloading cognitive demands onto external representations, thus freeing mental resources for higher-order regulation tasks (Nückles et al., 2020). This is particularly effective when combined with instructional support that guides learners' metacognitive engagement.

In digital learning environments, temporal learning analytics and trace-based modelling have emerged as powerful methods for capturing and analysing SRL behaviours in real time. Research has shown that high-performing learners in asynchronous online courses often demonstrate greater time management, deeper cognitive engagement, and reduced cognitive load, benefits that are partly attributed to the design and structure of these supportive technologies (Sun et al., 2023). Among these technologies, tools such as the Open Learner Model (OLM) and analytics dashboards embedded within learning management systems (e.g., Moodle, Canvas) serve a crucial role by making learning behaviours visible and actionable. These interfaces support learners' reflection and metacognitive monitoring by externalising data on progress and strategy use.

Additionally, responsive learning environments like the ROLE (Responsive Open Learning Environments) illustrate how personalisation and adaptive feedback can foster self-reflection. These platforms embed task planners, timers, and reflection prompts directly into the interface, thereby offloading complex regulatory tasks such as time management and self-evaluation. Longitudinal studies of such environments have shown promise in enhancing self-regulatory engagement across extended learning cycles (Renzel et al., 2015).

These technologies do more than assist with isolated SRL episodes; they act as amplifiers of learners' regulatory capacity, particularly by externalising key components like monitoring, reflection, and strategy selection. However, the design of cognitive offloading tools must be approached with caution: if learners become overly dependent on technological prompts, the opportunity to internalise and automatise SRL skills may be diminished. As such, careful attention must be paid to the instructional design of offloading tools to ensure they function as transitional supports rather than permanent substitutes (Nückles et al., 2020).

1.2 Cognitive Offloading and AI

However, this strategic reallocation of cognitive resources presupposes metacognitive oversight that contemporary AI systems may undermine. In the context of AI, students may increasingly externalise effortful thinking to GenAI systems, which can reduce cognitive strain but may also compromise learning quality over time (Grinschgl & Neubauer, 2022). These concerns are increasingly linked to the phenomenon of "cognitive offloading", where students externalise cognitive processes, such as memory, reasoning, and planning, completely to AI chatbots (Gerlich, 2025). While traditional forms of cognitive offloading, such as writing, externalise information to reduce internal cognitive load and free up mental resources for higher-order thinking, this strategic act is typically guided by metacognitive processes. The key consequence of such offloading is the potential reallocation of cognitive capacity away from simple "storage" and toward higher-order processes such as analysis, synthesis, and creative problem-solving.

There may be a sort of "metacognitive threshold" at which AI shifts from scaffolding to dependency: this transition arises when learners cease monitoring whether AI supports their learning and instead rely on it primarily for "answer extraction" (Fan et al., 2025). In this view, the risk is not AI per se but a weakening of metacognitive oversight that turns regulated offloading into unregulated delegation. More generally, AI support is beneficial when it functions as a temporary scaffold within self-regulatory cycles; it is potentially detrimental when it stabilises as a substitute for learners' planning, monitoring, and evaluation, especially in tasks they cannot yet manage independently.

AI today is not merely a passive support. Evidence suggests that habitual reliance on AI may result in reduced critical thinking and weakened metacognitive monitoring (Grinschgl & Neubauer, 2022; Zhai & Wibowo, 2024). While offloading has benefits such as freeing up working memory and facilitating strategic task performance, its overuse can lead to lower critical thinking skills, decreased metacognitive accuracy, and overreliance on AI-generated outputs (Gerlich, 2025; Goyal, 2025). In educational settings, this offloading often appears in the form of shallow help-seeking (e.g., copying answers from AI without analysis), a behaviour linked to diminished student agency and reduced learning gains (Zhai & Wibowo, 2024).

1.3 AI and SRL integration

Recent studies show that AI can enhance SRL when used strategically. For instance, guidance-based GenAI tools that require students to set goals before querying improve SRL and higher-order thinking (Lee et al., 2024), and AI-enabled formative assessments improve academic performance and regulation (Liao et al., 2024). AI literacy, when combined with SRL competencies, predicts both performance and well-being (Shi et al., 2025). At the same time, unregulated or indiscriminate use of AI may lead to what Deneen (2025) calls metacognitive sloth, a pattern of minimal planning and shallow processing driven by overdependence on AI's immediacy and convenience.

These outcomes reflect the importance of embedding AI use within full SRL cycles, including forethought, monitoring, and reflection and underscore the urgency of pedagogical frameworks that develop student agency alongside technological skill.

Study

1.4 Procedure and participants

A cross-sectional survey was conducted online with a convenience sample of students. Participation was voluntary and anonymous. The sample comprised only students who reported using AI for academic purposes (N = 134). Their ages ranged from 19 to 58 years (M = 25.3, SD = 7.82, Median = 23). Most participants identified as female (n = 113, 84.3%), followed by male (n = 20, 14.9%), with 1 respondent (.7%) selecting "prefer not to say". Regarding degree level, the sample was predominantly Bachelor's students (n = 112, 83.6%), with smaller proportions enrolled in Single-cycle Master's degrees (n = 16, 11.9%) and Master's degrees (n = 6, 4.5%). By disciplinary area, most were in Historical, Philosophical and Pedagogical sciences (n = 89, 66.4%), followed by Psychological sciences (n = 35, 26.1%), Information Engineering (n = 8, 6%), and small numbers in Mathematical sciences (n = 1, .7%) and Political and Social sciences (n = 1, .7%). Enrolment status was as follows: Second year Bachelor's 49 (36.6%), First year Bachelor's 36 (26.9%), Third year Bachelor's 26 (19.4%), Fifth year Single-cycle Master's/Second year Master's 17 (12.7%), Out of course (beyond nominal duration) 4 (3%), and Fourth year Single-cycle Master's/First year Master's 2 (1.5%). In sum, the cohort was chiefly composed of Bachelor's students (years 1-3 = 82.9%).

1.5 Instruments

Frequency of AI use for academic purposes. Students indicated how often they used AI tools specifically to perform academic tasks and activities. Response options were: Never; 1-2 times per month; 3-4 times per month; 2-3 times per week; Every day; Several times per day. Since we restricted the sample by excluding students who reported *Never* using AI for academic purposes, we retained the five ordered categories as an ordinal variable (coded 1-5 in ascending frequency).

Timing of AI use when facing study difficulties. Students answered: "When you encounter difficulties in studying, at what point do you turn to AI assistance?" Response options were: Immediately, as a first resource; After an initial attempt to solve the problem independently; After consulting course materials; After seeking help from peers; As a last resort; Never; It depends on the type of difficulty; and Other. The variable was analysed as a nominal outcome.

Self-Regulated Learning with AI Scale (SRL-AI). Developed for this study, the SRL-AI assessed how often students enact five SRL behaviours when using AI for learning: (1) setting specific learning goals before consulting AI; (2) monitoring understanding during interactions with AI; (3) adapting learning strategies based on feedback received from AI; (4) evaluating learning after using AI; and (5) reflecting on whether AI helped achieve learning goals[2]. Items were rated on a 1-5 Likert-type response scale (from 1 = Never to 5 = Always). A composite (SRL-AI_Mean) was computed as the mean of the five items, with higher scores indicating more frequent enactment of SRL behaviours during AI-supported learning.

[2] The psychometric properties of this five-item scale in the present sample are the following. The correlation matrix was found to be factorable (pseudo $\chi^2 = 237$, df = 10, $p < .001$; KMO = .83, all univariate KMOs ≥ .81). The subsequent exploratory factor analysis (EFA), conducted with principal-axis factoring extraction and oblique oblimin rotation, yielded a one-factor solution (parallel analysis, scree-test, and Kaiser-Guttman criterion) consistent with the expectations. The factor was saliently loaded by all five variables, with factor loadings ranging from .63 to .78, and it explained 50.8% of the variance in the correlation matrix. The factor also demonstrated good internal consistency reliability (McDonald's $\omega = .84$, Cronbach's $\alpha = .83$). These results support the use of a single composite.

1.6 Research questions

The study explored the following research questions (RQs) concerning students' SRL behaviours when using AI for learning.

- RQ1: To what extent do university students[3] enact SRL behaviours when using AI for learning?
- RQ2: Are there distinct profiles of students based on their SRL behaviours when using AI?
- RQ3: Is students' SRL when using AI associated with the frequency of AI use?
- RQ4: Is students' SRL when using AI associated with the timing of AI help-seeking upon encountering a study difficulty?

1.7 Data analysis

RQ1. Given the evidence[2] for a unidimensional structure of the *SRL-AI* scale, we computed a composite score (SRL-AI_Mean) by averaging the five items. We reported descriptives (N, Mean, SD, $25^{th}/50^{th}/75^{th}$ percentiles, skewness, kurtosis). Distributional assumptions were checked with the D'Agostino-Pearson test; as SRL-AI_Mean showed no departure from normality, the primary inference against the mid-scale point (3 = *Sometimes*) used a one-sample t-test (two-tailed, $\alpha = .05$). As a distribution-free robustness check, we also ran a Wilcoxon signed-rank test. Effect sizes were Cohen's d (t-test) and rank-biserial correlation (Wilcoxon).

RQ2. We investigated whether distinct SRL-AI student profiles exist among AI users by clustering the five items of the *SRL-AI* scale (i.e., goal setting, monitoring, adaptation, evaluation, and reflection), after z-standardising each variable. We applied *k*-means (Hartigan-Wong algorithm) with 50 random initialisations. To determine the number of clusters (k) we compared solutions for $k = 1$-4 using the gap statistic (with its bootstrap SEs), selecting the smallest k at which the gap first reached a clear increase and remained within overlapping error bars at larger k, and the elbow curve of total within-cluster dispersion, prioritising the first marked bend with diminishing returns thereafter. Having identified two clusters as the optimal solution, we proceeded to characterise them and test between-cluster differences. Because normality was mixed across clusters (D'Agostino-Pearson tests), between-cluster contrasts on each *SRL-AI* scale item and on the composite SRL-AI score (SRL-AI_Mean) were assessed non-parametrically with Mann-Whitney tests and effect sizes reported as rank biserial correlations.

RQ3. We assessed the association between SRL-AI_Mean and frequency of AI use (ordinal, non-equal steps) using two non-parametric approaches. First, we computed Spearman's ρ to quantify the monotonic relationship. Second, we tested for a directionally ordered trend across the five frequency categories with the Jonckheere-Terpstra (JT) test (H_1: higher frequency → higher SRL-AI_Mean), reporting the test statistic and the effect size as $r = z/\sqrt{N}$. As a descriptive complement, we compared the distribution of frequency across SRL-AI profiles (Lower vs Higher SRL with AI) using a Mann-Whitney test, specifying a one-tailed alternative (Higher > Lower) and reporting the rank-biserial correlation.

RQ4. To test whether students' SRL when using AI (SRL-AI_Mean) varies by timing of recourse to AI when encountering a study difficulty, we modelled timing as a nominal variable with four categories: S – Immediately (*Immediately, as a first resource*); T – After… (*After an initial self-attempt; After consulting course materials; After seeking help from peers*); U – It depends (*It depends*

[3] "Students" here refers to respondents who reported using AI to perform academic tasks and activities. Those who selected *Never* in response to the question about the frequency of AI use were excluded from this analysis.

on the type of difficulty); V – Last resort (*As a last resort*)[4]. The primary analysis was a linear regression with SRL-AI_Mean as the dependent variable and timing as the factor. As a distribution-free robustness check, we ran a Kruskal-Wallis test across S/T/U/V. As a complementary analysis, we also cross-tabulated the four timing categories (S, T, U, V) with the two SRL-AI profiles (Lower vs Higher) and tested their association with a chi-squared test.

Results

1.8 RQ1

Among AI users (N = 134), the composite SRL-AI score (SRL-AI_Mean) averaged just below the scale midpoint (Table 1). D'Agostino-Pearson normality test was non-significant ($K^2 = .43$, $p = .81$), indicating no evidence of deviation from normality in SRL-AI_Mean. Testing against the mid-scale value of 3 indicated no meaningful deviation: the one-sample *t*-test yielded $t(133) = -1.18$, $p = .242$, and the Wilcoxon signed-rank test likewise was non-significant (W = 3274, $p = .35$).

Overall, students who use AI for academic activities reported enacting SRL-AI behaviours with moderate regularity.

Table 1. SRL-AI_Mean descriptives

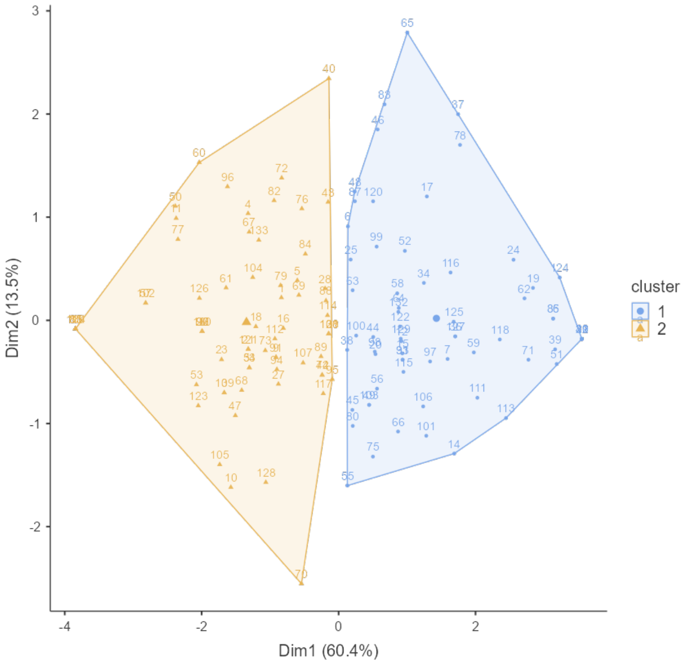
				Percentiles				
	N	**Mean**	**SD**	**25th**	**50th (Me)**	**75th**	**Skewness**	**Kurtosis**
SRL-AI_Mean	134	2.90	.940	2.40	3	3.60	-.0618	-.265

1.9 RQ2

Converging indices (gap statistic and elbow curve) supported a two-cluster solution. The final model yielded two balanced groups (Cluster 1, n = 65, 48.51%, within-cluster SS = 214; Cluster 2, n = 69, 51.49%, SS = 193) and between-cluster separation accounting for 38.8% of total dispersion (between SS/total SS = 258/665). Centroids were coherent and monotonic: one cluster scored below the sample mean on all SRL-AI behaviours (z from -.61 to -.67), the other above the mean (z from .57 to .63). To aid interpretation, we projected the observations (students) onto the first two PCA components computed to the same z-scores and overlaid the *k*-means partition. The resulting cluster plot (Figure 1) showed clear spatial separation primarily along Dim1 (60.4% of variance), with modest spread on Dim2 (13.5%). On the original 1-5 scale (see Table 2), the *Higher SRL with AI* profile reported means from 3.30 (adaptation) to 3.88 (reflection), whereas the *Lower SRL with AI* profile ranged from 1.71 (adaptation) to 2.48 (reflection).

Figure 1. Cluster plot

[4] The *Never* option was excluded; therefore N = 133 for those analyses.



Because normality was mixed across clusters (D'Agostino-Pearson tests), between-cluster contrasts on each *SRL-AI* scale item and on the composite SRL-AI score (SRL-AI_Mean) were assessed with Mann-Whitney tests. Differences were uniformly large: rank biserial correlations ranged from |.66| to |.74| for items and |1| for SRL-AI_Mean (Table 2). On the original 1-5 scale, *Higher SRL with AI* (Cluster 2) showed higher central tendency than *Lower SRL with AI* (Cluster 1) for every behaviour and for SRL-AI_Mean; see Table 2 and Figure 2.

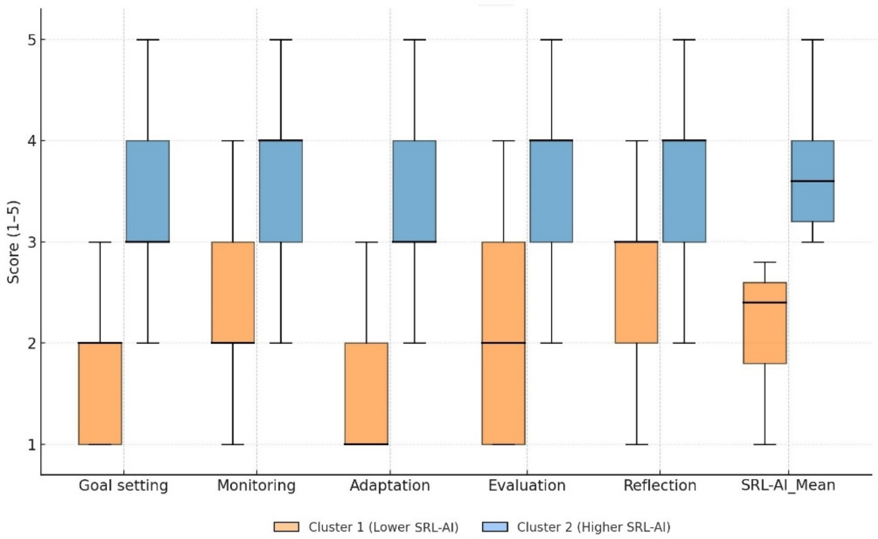
Taken together, these findings substantiated a clear separation between profiles, primarily in the overall level of SRL-AI behaviours rather than in their relative pattern.

Table 2. Students' SRL behaviours when using AI for learning: Descriptives by cluster and Mann-Whitney tests

					Percentiles			Mann-Whitney test		
	Cluster	**N**	**Mean**	**SD**	**25th**	**50th (Me)**	**75th**	**U**	***p***	**ES**
Goal setting	Higher SRL with AI	69	3.52	1.009	3	3	4	712	< .001	-.682
	Lower SRL with AI	65	2.02	1.053	1	2	2			
Monitoring	Higher SRL with AI	69	3.80	.833	3	4	4	759	< .001	-.662
	Lower SRL with AI	65	2.40	1.058	2	2	3			
Adaptation	Higher SRL with AI	69	3.30	.990	3	3	4	574	< .001	-.744
	Lower SRL with AI	65	1.71	.861	1	1	2			
Evaluation	Higher SRL with AI	69	3.67	.918	3	4	4	607	< .001	-.730
	Lower SRL with AI	65	2.05	1.007	1	2	3			
Reflection	Higher SRL with AI	69	3.88	.814	3	4	4	646	< .001	-.712
	Lower SRL with AI	65	2.48	.954	2	3	3			
SRL-AI_Mean	Higher SRL with AI	69	3.63	.547	3.2	3.6	4	0	<.001	-1
	Lower SRL with AI	65	2.13	.578	1.8	2.4	2.6			

Note. Tested hypothesis (two-tailed): Higher SRL with AI (Cluster 2) ≠ Lower SRL with AI (Cluster 1). Scale 1-5. ES = effect size calculated as rank biserial correlation.

Figure 2. SRL-AI behaviours by cluster (boxplots)



Overall, the two profiles traced a clear level-of-regulation gradient. *Lower SRL with AI* students reported infrequent engagement in the five SRL-AI practices (i.e., goal setting, monitoring, adaptation evaluation, and reflection), suggesting reliance on AI without systematic self-regulatory scaffolding – more delegation than regulation. In contrast, *Higher SRL with AI* students reported frequent and systematic engagement, with purposeful goal setting, iterative monitoring, post-use evaluation, consistent reflection, and adaptive strategy shifts – i.e., self-regulated use of AI. The near-parallel mean profiles indicated that the distinction concerns overall SRL-AI intensity rather than a reweighting of specific components.

1.10 RQ3

Association between SRL-AI and frequency. SRL-AI_Mean was positively associated with frequency of AI use with a small effect: Spearman $\rho = .175$, $p = .044$. A Jonckheere-Terpstra ordered trend test (H_1: higher frequency → higher SRL-AI_Mean) likewise indicated a small, positive trend: J-T statistic = 3866.5, $z = 1.978$, $p = .048$ (two-tailed), $r = .17$.

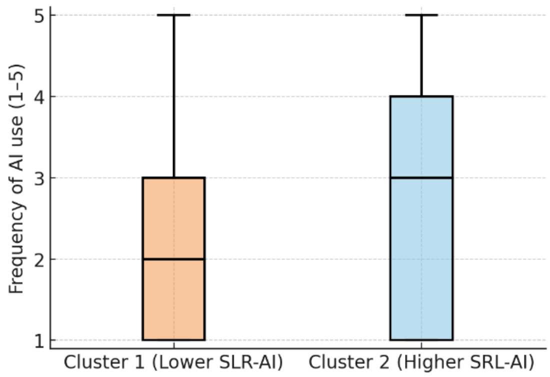
Frequency by SRL-AI profile. Students with *Higher SRL with AI* (Cluster 2) reported higher usage frequency than those with *Lower SRL with AI* (Cluster 1), with a small effect (Table 3; Figure 3).

Table 3. Frequency of AI use by cluster and Mann-Whitney test

			Percentiles			Mann-Whitney test		
	Cluster	**N**	**25th**	**50th (Me)**	**75th**	**U**	***p***	**ES**
Frequency of AI use	Higher SRL with AI	69	1	3	4	1864	= .04 (one-tailed)	-.169
	Lower SRL with AI	65	1	2	3			

Note. Tested hypothesis (one-tailed): Higher SRL with AI (Cluster 2) > Lower SRL with AI (Cluster 1). ES = effect size calculated as rank biserial correlation.

Figure 3. Frequency of AI use by cluster (boxplots)



Overall, students who reported more frequent AI use also tended to report slightly higher SRL behaviours when using AI for learning. The effect is small but consistent across rank correlation (Spearman), an ordered-trend test (Jonckheere-Terpstra), and a profile-based median comparison (Mann-Whitney). This pattern is associational, not causal: clusters were derived from SRL-AI behaviours, so the frequency difference by profile reflects convergent validity, not evidence that frequent use increases SRL-AI. Establishing causality would require longitudinal or experimental designs.

1.11 RQ4

Among AI users (N = 133[5]), SRL-AI_Mean did not differ by timing of AI help-seeking. In linear regression with Timing entered as a factor and SRL-AI_Mean as a dependent variable, model fit was small (R^2 = .029, Adjusted R^2 = .0065; AIC = 367, BIC = 381, RMSE = .926), and the omnibus ANOVA test was non-significant ($F(3,129) = 1.29$, p = .281). A distribution-free check converged: Kruskal-Wallis test showed that across timing categories S, T, U, and V, SRL-AI_Mean did not differ significantly ($\chi^2(3) = 3.26$, p = .353). Descriptives (Table 4) showed broadly similar central tendency across categories, noting the limited precision for S (n = 5). Moreover, the cross-tabulation of timing categories by SRL-AI cluster (*Lower SRL with AI* vs *Higher SRL with AI*) showed no significant association ($\chi^2(3) = 2.95$, p = .40), indicating that the distribution of students across *Immediately*, *After…*, *It depends*, and *Last resort* was broadly similar between the two profiles (Table 5).

Table 4. Descriptives of SRL-AI_Mean by timing of AI help-seeking among AI users

					Percentiles		
	Timing of AI help-seeking	**N**	**Mean**	**SD**	**25th**	**50th (Me)**	**75th**
SRL-AI_Mean	S (Immediately)	5	2.84	.261	2.6	2.8	3
	T (After…)	69	2.97	.796	2.4	3	3.6
	U (It depends)	35	3.03	1.077	2.5	3	3.7
	V (Last resort)	24	2.58	1.165	1.6	2.4	3.6

Table 5. Contingency table: Timing category by SRL-AI cluster

	SRL-AI cluster		
Timing of AI help-seeking	**Higher SRL with AI**	**Lower SRL with AI**	**Total**
T (After..)	39	30	69
U (It depends)	19	16	35
V (Last resort)	9	15	24

[5] See RQ2 results; *Never* option was excluded.

S (Immediately)	2	3	5
Total	69	64	133

Overall, among AI users, the frequency of students' SRL behaviours while using AI (i.e., SRL-AI_Mean) was not associated with the timing of AI help-seeking. In other words, students who turned to AI immediately, after self-attempt/consultation/peer help, conditionally, or as a last resort, showed comparable levels of SRL while using AI. This suggests that when students seek AI help, it is largely orthogonal to how self-regulated they are while using it, although small cell sizes for *Immediately* warrant cautious interpretation.

Discussion

Our findings suggest two broad ways in which students reported using AI for learning. On average, students engaged SRL behaviours – goal setting, monitoring, adaptation, evaluation, and reflection – with moderate regularity; however, a clear two-profile pattern emerged. One group reported infrequent, unsystematic use of these behaviours (*Lower SRL with AI*; *Lower-SRL-AI* students), while another reported frequent and systematic engagement (*Higher SRL with AI*; *Higher-SRL-AI* students).

This pattern is consistent with Pintrich's (2000, 2004) account of regulation of cognition across phases, e.g.: setting and activating task-specific goals before study (*forethought, planning, and activation*), monitoring one's understanding during task performance (*monitoring*), controlling and adjusting strategies as needed (*control*), and reflecting/evaluating outcomes to inform subsequent learning (*reaction/reflection*). In our data, the *Higher SRL with AI* profile was characterised by setting specific learning goals before consulting AI, monitoring understanding during AI interactions, adapting learning strategies in light of feedback received from AI, evaluating learning after using AI, and reflecting on whether AI helped to achieve learning goals – precisely the kinds of cognitive-regulatory actions envisaged by Pintrich. By contrast, the *Lower SRL with AI* profile reported these behaviours infrequently and unsystematically – with particularly weaker goal setting and monitoring, sparse adaptation of strategies, and only limited post-use evaluation and reflection. Overall, this profile seems to reflect minimal engagement in cognitive regulation during AI-supported study.

Read through Zimmerman's cyclical model of SRL (2011), the profiles differ in how fully students sustain the forethought → performance → self-reflection loop. *Higher-SRL-AI* students appear to sustain the whole cycle: they set concrete study goals before turning to AI (*forethought*), implemented strategies and monitored their understanding in real time during AI interactions, adjusting what they do as needed (*performance*), and then evaluated outcomes and reflected on whether AI contributed to achieving their goals (*self-reflection*). By contrast, *Lower-SRL-AI* students appear to engage only fragmentarily in the cycle: they showed minimal goal setting, tended to use AI more passively with limited monitoring and little control of strategies, and rarely engaged in evaluative or reflective follow-up. Overall, this profile appears to enter AI interactions with less forethought, engage more passively during performance, and reflect less afterwards.

Taken together, students in this sample appear to split between a more delegative pattern of AI use (*Lower SRL with AI*; "Delegators") and a more self-regulated pattern (*Higher SRL with AI*; "Self-regulators"), distinguished by how consistently they enact the core cognitive-regulatory processes before, during, and after AI use.

Two further results refine this picture. First, students who reported using AI more frequently also reported slightly higher SRL with AI. This pattern was modest in size, but it was consistent across analyses. We interpret this not as evidence that frequent use increases SRL-AI, but as convergent validity: students who habitually plan, monitor, control, and reflect may also be the ones who return to AI more often as a purposeful study aid. Second, when students turned to AI during difficulty (immediately, after other attempts, conditionally, last resort), it was not associated with their SRL-AI. Timing, in other words, did not discriminate between the two SRL-AI profiles in our sample. This suggests that the educationally meaningful question is less "when should students ask AI for help?" and more "with which self-regulatory behaviours do they engage when they do?".

This interpretation is consistent with recent reviews arguing that AI supports learning best when it is embedded in learner-centred SRL cycles rather than allowed to drive them. Chang and Sun (2024), in a systematic review of AI-mediated language learning, argue that AI can function as a mind tool within Zimmerman's cyclical SRL framework, but only if learners actively engage in goal setting, monitoring, and reflection. Otherwise, AI use degenerates into what they describe as "shallow answer harvesting", where students bypass self-regulation and rely on surface-level outputs. This distinction could reflect the gap between *Delegators* and *Self-regulators* in our findings: "delegative" use risks disrupting the SRL cycle, while "self-regulated" use supports it and could use AI to amplify planning, monitoring, control, and reflection. Similarly, Lan and Zhou (2025), in their systematic review of AI-empowered SRL in higher education, show that AI can indeed support forethought, performance, and reflection phases, but outcomes crucially depend on whether the locus of agency remains with the student. When AI becomes the primary driver of decisions, an AI-centred model that could resemble the Delegators profile, students risk losing self-efficacy and autonomy. By contrast, when AI acts as a scaffold that complements student agency, a human-centred model that could resemble the Self-regulators profile, it enhances autonomy and self-efficacy.

These behavioural profiles should also be read in light of recent empirical research on how generative AI influences learning outcomes through deeper psychological mechanisms and shows that AI's academic benefits are not merely dependent on usage frequency or timing, but on how usage shapes cognitive offloading and shared metacognitive engagement (Goyal, 2025; Borge et al., 2024). When AI tools are structured to encourage reflection, argumentation, and collaboration, they can amplify learners' regulatory capacities (Xu & Qiao, 2025; Zhao & Sheng, 2025). However, unstructured use can foster dependence, reduce metacognitive effort, and offload key aspects of learning prematurely (Grinschgl & Neubauer, 2022). As such, student agency, AI literacy, and socially supported learning environments are essential moderators of AI's educational impact. These factors must be addressed in both design and pedagogy to ensure AI is used to scaffold, not substitute, the "core" regulatory skills.

In conclusion, the literature indicates that AI in education is not inherently beneficial or detrimental; rather, its effects depend on the quality of self-regulation and the strategic engagement of the learner. For students who regulate their learning intentionally, AI can become a resource that supports cognitive flexibility, reflective thinking, and goal-oriented study. For students with weak SRL habits, however, the same tools may risk reinforcing dependency, bypassing key regulatory processes, and diminishing opportunities for higher-order learning and reflective engagement. Future research should examine how to design AI-enhanced learning environments that integrate AI literacy education and promote self-regulated AI use by students, in order to support all students, especially those most at risk of "delegating" their learning to AI tools.

Conclusions

Educational implications. From an educational perspective, the findings suggest that educators should focus less on how much students use AI and when they turn to AI, and more on how they use it. The contrast between delegative and self-regulated use underscores the need for explicit guidance: students should be supported in using AI for feedback, exploration, and reflection rather than as a shortcut to bypass learning. The challenge for Higher Education lies in guiding students toward self-regulated use, where AI acts as a learning scaffold, rather than allowing patterns of delegative use that risk undermining students' critical and reflective engagement. As Lan and Zhou (2025) emphasised, maintaining *human-centred SRL* is essential and should remain the predominant form of SRL, especially when contrasted with *AI-centred SRL*. Practical steps could include designing tasks that require students to compare their own reasoning with AI outputs, or embedding reflection prompts whenever AI is used as study support, integrating AI literacy with SRL training, and helping students shift from delegative to self-regulated AI use. This approach will be critical to ensuring that AI contributes to learners' agency, critical thinking, and long-term educational goals.

Limitations and future research. The present study had some limitations. First, it relied on self-reported survey data, which may be affected by recall bias or social desirability, and may not fully mirror actual behaviours. Second, its cross-sectional design limits causal inference: while higher SRL-AI was associated with more frequent AI use, we cannot determine whether increased AI use fosters SRL-AI or whether more self-regulated students simply use AI more. Third, these findings should be interpreted mostly as sample-specific rather than population-wide. The study relied on a convenience sample that was discipline-skewed (predominantly Historical, Philosophical and Pedagogical; and Psychological sciences), drawn from a single institutional context, and – notably – reported only moderate overall AI use. Patterns may therefore differ in other institutions, cultures, or disciplines, especially those with more technical AI applications (e.g., engineering). Accordingly, the results characterise this cohort and should not be treated as generalised estimates for all students. Fourth, the frequency measure was ordinal with non-equal steps, which constrains modelling choices and may attenuate effect estimates. Future research should combine surveys with behavioural data (e.g., log files of AI interactions), adopt longitudinal or experimental designs to observe how AI use and SRL-AI evolve over time and test causal mechanisms, broaden disciplinary and institutional coverage, and explicitly examine possible differences between disciplines. Robustness checks with alternative operationalisations of frequency (e.g., finer-grained or logged measures) would also strengthen inference.

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