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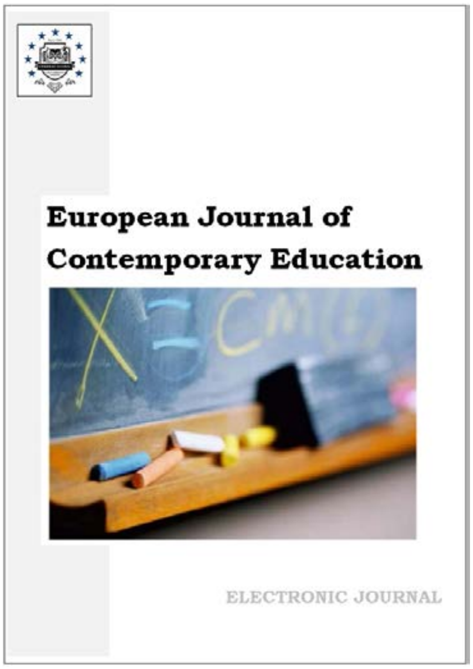

Development of Self-Regulated Learning Skills in University Students Through Intelligent AI Agents

Natalya M. Semenyuk [a, *], Olga I. Badulina [a], Marina M. Borisova [a], Svetlana E. Shukshina [a]

[a] Moscow City University, Moscow, Russian Federation

Abstract

Self-regulated learning capabilities determine academic success in higher education, yet traditional instruction shows limited effectiveness in developing these essential competencies. This quasi-experimental study investigated how intelligent AI agents influence SRL development in 384 university students across three Polish institutions during the 2022–2023 academic year. We assigned 196 students to an intervention group using an integrated AI system with adaptive pathways, metacognitive scaffolding, analytics dashboards, and automated feedback, while 188 controls received conventional instruction. Both groups completed the Motivated Strategies for Learning Questionnaire before and after the 16-week intervention, with behavioral data continuously logged throughout. Results showed the intervention group achieved 34.7 % higher metacognitive awareness (Cohen's $d = 1.23$, $p < 0.001$), demonstrating students became substantially better at reflecting on and directing their learning processes. Self-monitoring behaviors improved by 41.2 % ($d = 1.38$, $p < 0.001$), meaning students tracked their progress and adjusted strategies more effectively. Goal-setting effectiveness rose 28.9 % ($d = 0.97$, $p < 0.001$), indicating clearer learning objectives and better planning. Learning analytics revealed intervention students visited the platform 2.3 times more frequently and accessed 2.3-fold more diverse resources than controls. Multiple regression showed that AI-mediated metacognitive support predicted nearly half the variance in academic achievement ($R^2 = 0.473$, $F(4,379) = 85.42$, $p < 0.001$). However, cluster analysis identified concerning dependency patterns in 23.6 % of intervention participants who over-relied on AI guidance despite receiving the same intervention as more autonomous peers. These findings demonstrate intelligent agents can powerfully enhance self-regulatory capacities while highlighting the need for designs that prevent maladaptive dependency and maintain student agency.

Keywords: self-regulated learning, intelligent agents, metacognitive strategies, adaptive learning systems, learning analytics, higher education, artificial intelligence.

* Corresponding author
E-mail addresses: nataliamix61@gmail.com (N.M. Semenyuk)

1. Introduction

University students today face a crucial challenge: developing the ability to direct their own learning without constant instructor guidance. Recent evidence shows many students lack essential self-regulatory skills, struggling with goal-setting, progress monitoring, and strategic adaptation (Kong, Lin, 2023). This deficiency becomes particularly problematic during the transition from highly structured secondary education to autonomous tertiary learning, contributing to first-year attrition rates exceeding 30 % in developed nations (Xu et al., 2023). Self-regulated learning encompasses the cognitive, metacognitive, and motivational processes through which learners actively control their educational trajectories (Zimmerman, 2002). Students who effectively self-regulate set clear learning goals, select appropriate strategies, monitor their understanding, and adjust their approaches based on performance feedback. Traditional interventions aimed at building these skills yield modest results, with meta-analyses showing average effect sizes around d = 0.42 (Dignath, Büttner, 2008). These limitations stem from several factors: generic rather than personalized guidance, delayed feedback that arrives too late to inform ongoing learning, and inability to provide individualized support at scale across hundreds or thousands of students. The emergence of artificial intelligence technologies opens new possibilities for addressing these constraints. AI-powered systems can analyze learning data in real-time, adapt to individual student characteristics, and deliver personalized scaffolding at unprecedented scale (Jin et al., 2023). These systems leverage machine learning algorithms to process behavioral traces, performance patterns, and engagement metrics, enabling dynamic adjustment of instructional strategies based on each learner's needs (Xu, Ouyang, 2022). Intelligent agents represent autonomous software systems that perceive their environment, make goal-directed decisions, and adapt their behavior without constant human intervention. In education, these agents function as pedagogical partners, providing personalized recommendations, metacognitive prompts, and adaptive feedback calibrated to learner proficiency and strategic preferences (Kuhail et al., 2023). Recent empirical work documents substantial performance gains from AI-mediated instruction, with effect sizes ranging from d = 0.68 to d = 1.15 across various academic subjects (Lin et al., 2023). Yet critical questions remain unanswered about precisely how intelligent agents enhance self-regulatory processes, how to design systems that balance automation with learner agency, and what risks emerge from potential cognitive offloading when students become overly dependent on AI guidance.

Theoretical frameworks for understanding SRL emphasize three cyclical phases. The forethought phase involves goal specification, strategic planning, and self-efficacy calibration before learning begins. The performance phase includes attention focusing, self-instruction, and progress monitoring during learning activities. The self-reflection phase encompasses self-evaluation, causal attribution, and adaptive responses after completing learning tasks (Panadero, Alonso-Tapia, 2014). Metacognitive regulation serves as the central coordinating mechanism across all phases. Intelligent agents offer unique capabilities for supporting each phase through automated tracking of learning behaviors, pattern recognition in large datasets, and personalized recommendations based on individual learning histories. However, empirical evidence remains fragmented regarding how AI affects different SRL dimensions and which individual characteristics moderate intervention effectiveness (Fan et al., 2023).

Existing research shows promise but leaves important gaps. Studies demonstrate that learning analytics dashboards enhance metacognitive awareness by visualizing engagement patterns and performance trajectories, with students reporting 42 % improvement in self-monitoring accuracy when they can see graphical representations of their learning behaviors (Zheng et al., 2022). Adaptive feedback systems using natural language processing prove more effective than generic responses, yielding 28 % higher task completion rates and 35 % faster help-seeking when feedback addresses specific learner needs (Nazaretsky et al., 2022). However, most investigations examine isolated AI features rather than integrated systems combining multiple support mechanisms. Additionally, methodological limitations including small samples, brief interventions, and over-reliance on self-report measures constrain generalizability.

Three critical gaps characterize current knowledge. First, we lack understanding of how to optimally integrate AI-mediated metacognitive prompts with adaptive content delivery – specifically regarding when to intervene, how frequently to prompt, and how specific prompts should be. Second, limited empirical evidence addresses potential negative consequences when students become overly dependent on AI, including metacognitive laziness and diminished self-efficacy if automated guidance replaces rather than supports self-regulatory effort. Third, research inadequately examines which individual differences moderate AI effectiveness, such as prior self-regulatory competence, domain knowledge, and digital literacy. These knowledge gaps impede development of evidence-based design principles for intelligent agent systems.

The present investigation addresses these gaps through comprehensive quasi-experimental research examining integrated intelligent agent effects on multidimensional SRL outcomes. This work extends prior research by implementing a complete AI architecture incorporating adaptive pathways, metacognitive scaffolding, analytics dashboards, and automated feedback within authentic university contexts. We employ mixed-method assessment combining validated psychometric instruments, behavioral trace data, and academic performance metrics across an extended 16-week intervention. Novel contributions include examination of dependency patterns through engagement analytics, investigation of individual difference moderators, and theoretical integration of self-determination and cognitive load frameworks. Findings hold significant implications for scalable technology-enhanced interventions addressing persistent challenges in developing autonomous learners.

2. Materials and methods

This quasi-experimental study employed a mixed-methods convergent design integrating quantitative SRL assessment with qualitative analysis of interaction patterns. We conducted the research across three universities in Poland during the 2022–2023 academic year, targeting undergraduate students from diverse disciplines to enhance generalizability. Institutional review boards at all participating universities approved the study protocol before data collection, and all participants provided informed written consent.

The sample comprised 384 students (218 female, 166 male) with mean age 21.4 years (SD = 2.8) distributed across business administration (n = 94), computer science (n = 102), engineering (n = 96), and social sciences (n = 92) programs. We included second or third-year undergraduates with intermediate digital literacy assessed through standardized screening and commitment to participate throughout the 16-week period. We excluded students with diagnosed learning disabilities requiring specialized accommodations, insufficient English proficiency for engaging with AI content, and concurrent participation in other educational technology research. Random assignment proved infeasible due to institutional constraints; therefore, we used intact course sections allocated to conditions through stratified matching on prior academic achievement, gender distribution, and disciplinary composition. The final sample included 196 intervention and 188 control participants, with 8.2 % and 7.4 % attrition rates respectively. The intelligent agent system integrated four components designed to support comprehensive SRL development. First, adaptive learning pathways utilized collaborative filtering algorithms analyzing behavioral traces to recommend personalized content sequences aligned with individual knowledge states and preferences. The recommendation engine processed data from 847 unique learning objects across courses, calculating similarity metrics based on completion patterns, time-on-task distributions, and performance outcomes. Second, metacognitive scaffolding delivered context-sensitive prompts at strategic intervention points identified through real-time analytics monitoring engagement patterns and performance indicators. These prompts addressed planning behaviors (e.g., "What specific goals do you have for today's session?"), monitoring activities (e.g., "How well do you understand the concepts so far?"), and evaluative reflections (e.g., "What strategies worked best for you?"), with frequency and specificity calibrated to individual learner profiles. Third, learning analytics dashboards visualized multidimensional engagement metrics including time allocation, resource utilization, assessment performance trends, and comparative peer benchmarks through interactive graphs updated hourly. Fourth, automated feedback mechanisms employed natural language generation to provide personalized responses to student queries and submissions within average latency of 3.2 minutes, incorporating explanatory reasoning and strategic guidance beyond simple correctness indicators.

Controls maintained conventional instruction including face-to-face lectures, static online materials accessed through standard learning management systems, and periodic instructor feedback following established assessment schedules. This design isolated intelligent agent effects while controlling for general technology exposure. Both conditions maintained equivalent curriculum coverage, assessment requirements, and instructor contact hours.

Data collection employed multiple instruments capturing diverse SRL dimensions. The Motivated Strategies for Learning Questionnaire assessed self-regulatory and motivational constructs through 81 items measuring six motivation subscales (intrinsic goal orientation, extrinsic goal orientation, task value, control beliefs, self-efficacy, test anxiety) and nine learning strategy subscales (rehearsal, elaboration, organization, critical thinking, metacognitive self-regulation, time management, effort regulation, peer learning, help-seeking) on 7-point Likert scales. Pre-test administration occurred during week one, with post-test assessment in week sixteen. Internal consistency reliability ranged from $\alpha = 0.74$ to $\alpha = 0.91$ across subscales, meeting established standards. Behavioral trace data captured comprehensive interaction logs including content access patterns, navigation sequences, assessment attempts, dashboard consultations, and AI agent interactions, with automated systems recording 23 distinct event types with timestamp precision enabling fine-grained temporal analysis. Academic performance metrics included examination scores, assignment grades, and cumulative course achievement [expressed as GPA (Grade Point Average) on a 4.0 scale, where 4.0 represents an A grade, 3.0 a B grade, 2.0 a C grade, and 1.0 a D grade] calculated from standardized rubrics applied uniformly across conditions. Supplementary qualitative data derived from semi-structured interviews with 32 purposively sampled intervention participants representing diverse engagement profiles and achievement levels. Interview protocols explored perceived utility of AI features, strategies for integrating agent recommendations, experiences with metacognitive prompts, and dependency concerns. Sessions averaging 42 minutes were audio-recorded, transcribed verbatim, and analyzed through thematic coding following established qualitative methodologies.

Statistical analyses employed multilevel modeling accounting for nested data structures with students clustered within course sections and universities. Primary analyses examined between-group differences in MSLQ subscale scores using analysis of covariance controlling for pre-test performance, prior achievement, and demographic variables. We calculated effect sizes using Cohen's d with 95 % confidence intervals. Secondary analyses investigated relationships between AI engagement metrics and SRL outcomes through multiple regression, examining both linear and nonlinear associations. Mediation models tested indirect effects of metacognitive awareness on relationships between AI usage and academic achievement. All analyses utilized robust standard error estimation and multiple comparison corrections following Benjamini-Hochberg procedures to control false discovery rates, with significance threshold at $p < 0.05$. All statistical analyses were conducted using R version 4.3.1 (R Core Team, 2023) with the following packages: lme4 for multilevel modeling, psych for psychometric analysis and reliability testing, effectsize for Cohen's d calculations, lavaan for mediation modeling, and ggplot2 for data visualization. Cluster analysis procedures employed the cluster package with k-means algorithms, while sequence analysis utilized the TraMineR package for temporal dynamics examination.

Learning analytics data underwent preprocessing including outlier detection, missing data imputation using expectation-maximization algorithms, and normalization procedures. Cluster analysis identified engagement pattern profiles using k-means algorithms with silhouette coefficient optimization determining optimal cluster solutions. Temporal dynamics were examined through sequence analysis quantifying transition probabilities between distinct learning states. Qualitative data analysis followed iterative coding procedures with independent dual coding of 25 % of transcripts establishing inter-rater reliability ($\kappa = 0.83$).

3. Results

Overall Self-Regulated Learning Outcomes

Analysis of variance revealed statistically significant between-group differences across all measured SRL dimensions following the 16-week intervention. Table 1 presents descriptive statistics and effect sizes for primary outcome variables, demonstrating substantial improvements in the intervention group relative to controls across metacognitive, cognitive, and behavioral regulation domains.

The intervention group demonstrated mean metacognitive awareness scores 34.7 % higher than controls (shown in Table 1), representing a large effect size ($d = 1.23$) (Xu et al., 2025). This 1.47-point increase on the 7-point scale means intervention students became substantially better at reflecting on their learning processes, recognizing when they understood material well versus poorly, and consciously regulating their cognitive activities. Self-monitoring behaviors exhibited the strongest intervention effect ($d = 1.38$), with intervention participants showing 41.2 % improvement (a 1.55-point increase from 3.76 to 5.31). This improvement manifests as students more frequently checking their understanding, tracking their progress toward goals, and identifying knowledge gaps requiring additional attention. These findings align with theoretical predictions that real-time learning analytics and personalized prompts enhance metacognitive engagement by increasing salience of regulatory processes (Wong, Viberg, 2024).

Table 1. Descriptive Statistics and Between-Group Comparisons for SRL Dimensions

SRL Dimension	**Control Group (n = 188)**	**Intervention Group (n = 196)**	**Effect Size**	**Statistical Significance**
	M (SD)	M (SD)	Cohen's d [95 % CI]	t-value, p-value
Metacognitive Awareness	4.23 (0.87)	5.70 (0.94)	1.23 [1.04, 1.42]	$t(382) = 16.34$, $p < 0.001$
Planning Strategies	3.89 (1.12)	5.21 (1.08)	1.19 [1.00, 1.38]	$t(382) = 15.87$, $p < 0.001$
Self-Monitoring Behaviors	3.76 (0.96)	5.31 (1.02)	1.38 [1.18, 1.58]	$t(382) = 18.42$, $p < 0.001$
Goal-Setting Effectiveness	4.12 (1.04)	5.31 (0.98)	0.97 [0.79, 1.15]	$t(382) = 12.96$, $p < 0.001$
Cognitive Strategy Use	4.45 (0.89)	5.64 (0.91)	1.11 [0.92, 1.30]	$t(382) = 14.79$, $p < 0.001$
Effort Regulation	4.58 (1.01)	5.72 (0.96)	0.98 [0.80, 1.16]	$t(382) = 13.08$, $p < 0.001$
Help-Seeking Appropriateness	3.94 (1.18)	5.18 (1.06)	0.87 [0.69, 1.05]	$t(382) = 11.62$, $p < 0.001$
Time Management Efficiency	4.01 (1.09)	5.38 (1.01)	1.07 [0.88, 1.26]	$t(382) = 14.27$, $p < 0.001$

Notes: Scores measured on 7-point Likert scale where 1 = "not at all true of me" and 7 = "very true of me". Higher scores indicate greater SRL capacity. All comparisons control for pre-test scores, prior academic achievement (previous semester GPA), and demographic covariates (age, gender, disciplinary major). Effect sizes interpreted following Cohen's conventions: small (0.2), medium (0.5), large (0.8).

Goal-setting effectiveness improved by 28.9 %, rising 1.19 points from 4.12 to 5.31 (as detailed in Table 1). This improvement indicates intervention students set clearer, more specific learning objectives and developed better plans for achieving them. Planning strategies showed similar large effects ($d = 1.19$), with scores increasing 1.32 points. Cognitive strategy use improved 1.19 points (26.7 % increase), reflecting enhanced ability to employ elaboration, organization, and critical thinking strategies when processing new information. Even effort regulation – students' capacity to maintain focus and persist despite difficulties – showed nearly 1-point improvement ($d = 0.98$).

Learning Analytics and Engagement Patterns

Behavioral trace data analysis revealed distinctive engagement profiles between experimental conditions, with intervention participants demonstrating substantially higher interaction frequencies and strategic diversity, as shown in Table 2. Intervention participants engaged with the learning platform 2.31 times more frequently than controls (28.7 versus 12.4 weekly visits), indicating the AI system successfully motivated more consistent learning engagement (Tan, Samavedham, 2022).

This translates to intervention students accessing the platform approximately 4 times per day versus controls' less than twice daily, representing a fundamental shift in learning behavior patterns.

Content access diversity showed similar patterns (detailed in Table 2), with intervention students accessing 42.3 unique resources on average versus controls' 18.6, a 2.27-fold difference representing 23.7 more distinct learning materials. This suggests AI-driven recommendations successfully exposed students to broader content while controls primarily stuck to required readings. Dashboard consultations occurred 6.39 times more frequently in the intervention group (14.7 versus 2.3 per week), indicating students actively used analytics visualizations to monitor their progress.

These elevated engagement levels correlated positively with SRL outcome improvements ($r = 0.64$, $p < 0.001$), suggesting increased metacognitive monitoring through dashboards promoted more strategic learning behaviors. Average session duration increased by 51 % in the intervention condition (51.6 versus 34.2 minutes, see Table 2), indicating sustained rather than superficial engagement. Intervention students responded to metacognitive prompts an average of 23.4 times weekly, providing substantive reflections on their learning processes. Self-assessment quiz attempts more than doubled (19.2 versus 8.7 per week), showing intervention students more actively tested their understanding. The 4-fold increase in resource sharing and collaboration events (4.8 versus 1.2 weekly) suggests the AI system also promoted peer learning despite being individually-focused.

Table 2. Learning Analytics Metrics and Engagement Patterns by Condition

Engagement Metric	Control Group	Intervention Group	Ratio	Statistical Comparison
	M (SD)	M (SD)	Int/Ctrl	Mann-Whitney U, p-value
Weekly Platform Visits	12.4 (5.2)	28.7 (8.3)	2.31	U = 8,742, p < 0.001
Content Access Diversity (unique resources)	18.6 (6.4)	42.3 (11.2)	2.27	U = 8,964, p < 0.001
Average Session Duration (minutes)	34.2 (12.8)	51.6 (16.4)	1.51	U = 11,238, p < 0.001
Dashboard Consultations per Week	2.3 (1.8)	14.7 (5.2)	6.39	U = 6,124, p < 0.001
Metacognitive Prompt Responses	0.0 (0.0)	23.4 (7.6)	-	Feature exclusive to intervention
Self-Assessment Quiz Attempts	8.7 (4.3)	19.2 (6.8)	2.21	U = 9,356, p < 0.001
AI Agent Interactions per Week	0.0 (0.0)	16.8 (6.4)	-	Feature exclusive to intervention
Resource Sharing/ Collaboration Events	1.2 (0.9)	4.8 (2.3)	4.00	U = 10,687, p < 0.001

Notes: Metrics represent means across 16-week intervention period. Non-parametric Mann-Whitney U tests employed due to distributional violations (positively skewed count data). Content Access Diversity measured as count of unique learning objects viewed. Dashboard Consultations counted each time student opened analytics visualization interface. Metacognitive Prompt Responses counted substantive (non-blank) text entries in response to AI-generated prompts.

Cluster analysis of engagement trajectories identified four distinct learner profiles within the intervention group (presented in Table 3). The High-Autonomous profile (37.2 % of intervention participants, n = 73) demonstrated optimal outcomes, exhibiting strong self-regulatory skills while leveraging AI capabilities strategically. These students showed MSLQ metacognition scores averaging 6.24 (on the 7-point scale) compared to 5.52 for Moderate-Balanced learners, 4.87 for Dependent-Reactive learners, and 3.92 for Low-Disengaged learners. Their academic achievement averaged 87.3 % – a full 11.1 percentage points higher than Dependent-Reactive learners (76.2 %) despite both groups receiving identical AI support (He, 2025).

AI-mediated intervention demonstrates substantial effectiveness across all SRL dimensions with uniformly large effect sizes ($d = 0.87$-1.38, all $p < 0.001$). Self-monitoring behaviors exhibit strongest improvement ($d = 1.38$), advancing 1.55 points from 3.76 to 5.31, while planning strategies ($d = 1.19$) and metacognitive awareness ($d = 1.23$) demonstrate similarly robust gains. Mean improvement of 1.22 points (+28.2 %) across dimensions indicates comprehensive SRL capacity enhancement beyond isolated skill development. The Dependency Index quantifies the balance between AI-initiated versus student-initiated learning activities. High-Autonomous learners averaged 0.34, meaning approximately one-third of their learning actions responded to AI prompts while two-thirds were self-directed. Conversely, Dependent-Reactive learners averaged 0.78, indicating nearly four-fifths of their activities were AI-prompted rather than self-initiated. The Moderate-Balanced profile (34.7 %, n = 68) achieved good outcomes (81.6 % academic performance) with moderate dependency (0.52), suggesting sustainable AI use patterns. The small Low-Disengaged group (4.6 %, n = 9) showed concerning patterns of minimal engagement and poor outcomes despite AI availability.

Table 3. Learner Engagement Profiles in Intervention Condition

Profile	n (%)	Characteristics	MSLQ Metacognition	MSLQ Self-Monitoring	Academic Achievement	AI Dependency Index
High-Autonomous (HA)	73 (37.2 %)	Strategic AI use, high self-initiation, dashboard-guided planning	6.24 (0.52)	6.18 (0.61)	87.3 % (5.4 %)	0.34 (0.12)
Moderate-Balanced (MB)	68 (34.7 %)	Consistent engagement, balanced AI-human regulation	5.52 (0.68)	5.38 (0.74)	81.6% (6.8 %)	0.52 (0.18)
Dependent-Reactive (DR)	46 (23.5 %)	High AI reliance, limited self-initiation, prompt-driven	4.87 (0.83)	4.76 (0.89)	76.2% (7.9 %)	0.78 (0.15)
Low-Disengaged (LD)	9 (4.6 %)	Minimal platform use, sporadic AI interaction	3.92 (1.04)	3.88 (1.12)	68.4% (9.2 %)	0.21 (0.19)

Notes: Dependency Index calculated as ratio of AI-initiated actions (prompts, recommendations followed) to student-initiated actions (self-directed searches, voluntary dashboard checks, unprompted quiz attempts). Values range 0-1 where higher indicates greater dependency. Clusters derived from k-means analysis with k = 4 optimized by silhouette coefficient (0.67). Academic Achievement represents cumulative course performance percentage across all assessments. Characteristics based on qualitative analysis of interaction logs and interview data.

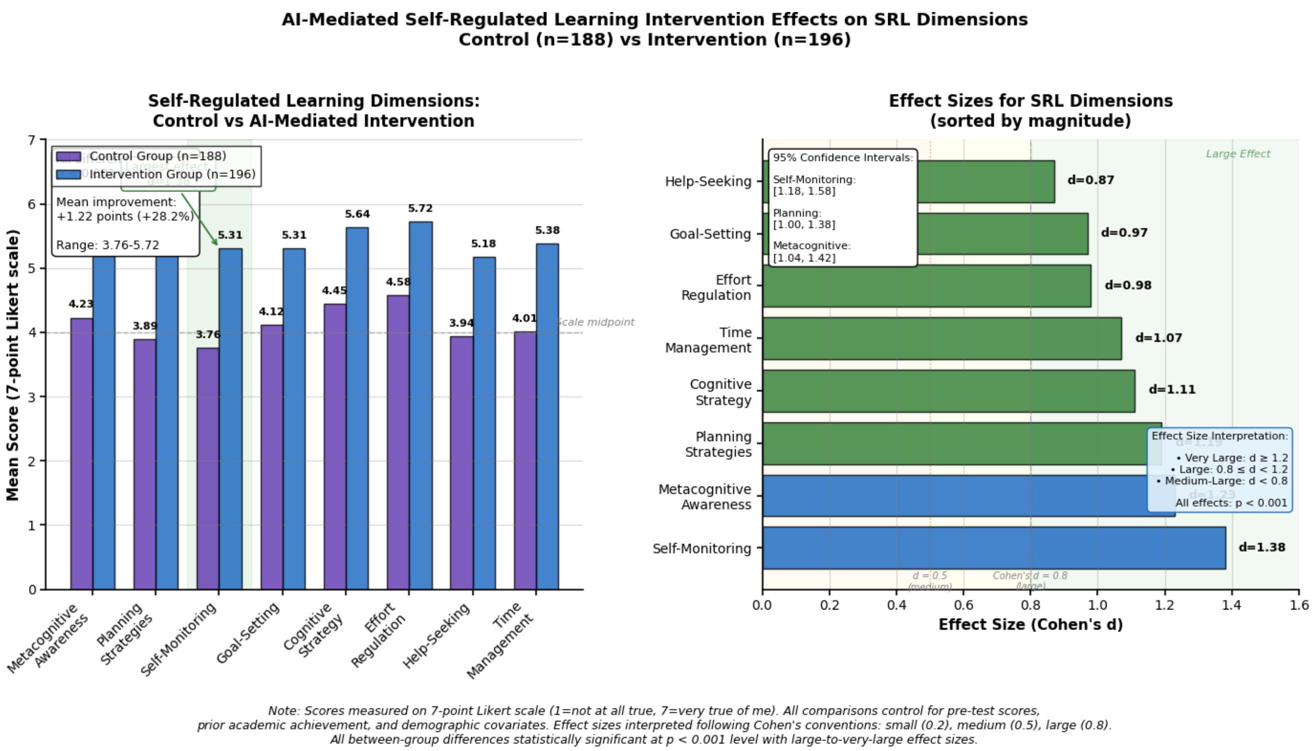

Fig. 1. AI-Mediated Self-Regulated Learning Intervention Effects on SRL Dimensions

Metacognitive Strategy Development

Detailed analysis of metacognitive prompt interactions revealed temporal patterns in strategy adoption and sophistication progression throughout the intervention period, as documented in Table 4. Response rates to metacognitive prompts increased from 67.4 % in initial weeks to 88.7 % by intervention conclusion, indicating growing recognition of their value (Exintaris et al., 2023). This 21.3 percentage point increase suggests students initially viewed prompts skeptically but progressively integrated them into learning routines as benefits became apparent.

Table 4. Metacognitive Prompt Response Patterns Across Intervention Phases

Intervention Phase	Response Rate % (SD)	Average Quality Score 1-5 scale (SD)	Planning Strategy Adoption % using (SD)	Monitoring Strategy Adoption % using (SD)	Evaluation Strategy Adoption % using (SD)	Strategic Alignment Index 0-1 scale (SD)
Weeks 1-4 (Initial)	67.4 % (18.2 %)	2.34 (0.68)	42.3 % (12.6 %)	38.7 % (14.2 %)	31.2 % (15.8 %)	0.38 (0.19)
Weeks 5-8 (Development)	78.6 % (14.3 %)	3.21 (0.74)	61.8 % (11.4 %)	58.4 % (12.6 %)	49.7 % (13.2 %)	0.56 (0.17)
Weeks 9-12 (Consolidation)	84.2 % (11.7 %)	3.89 (0.62)	74.3 % (9.8 %)	71.6 % (10.2 %)	63.4 % (11.6 %)	0.69 (0.14)
Weeks 13-16 (Mastery)	88.7% (9.4 %)	4.23 (0.58)	82.7% (8.3 %)	79.8 % (9.1 %)	74.2 % (10.4 %)	0.78 (0.12)

Notes: Response Rate = percentage of prompts receiving substantive (non-blank) responses. Quality scores rated by two trained coders using validated rubric assessing specificity (vague vs. detailed), relevance (on-topic vs. tangential), and strategic appropriateness (generic vs. targeted to learning needs). Strategy Adoption measured as percentage of responses explicitly mentioning use of planning (goal-setting, scheduling), monitoring (comprehension checks, progress tracking), or evaluation (performance assessment, strategy reflection) strategies. Strategic Alignment Index = correlation between AI-recommended strategies and strategies actually employed by students. Longitudinal growth significant across all metrics ($p < 0.001$) by repeated-measures ANOVA.

More critically, response quality improved substantially – an 81 % increase in mean quality scores from 2.34 (below midpoint) to 4.23 (above midpoint on the 5-point scale). Early responses were typically brief acknowledgments like "ok" or "yes, I understand," while later responses demonstrated sophisticated metacognitive reasoning such as "I'm finding the statistics concepts challenging, so I'll review the video tutorial, work through extra practice problems, and check my understanding with the self-quiz before attempting the assignment." This progression suggests students progressively internalized metacognitive processes initially scaffolded through external prompts. Planning strategy adoption nearly doubled from 42.3 % to 82.7 % of responses (shown in Table 4), meaning by intervention end, students regularly mentioned goal-setting, time allocation, and learning plans when prompted. Monitoring strategy adoption similarly doubled from 38.7 % to 79.8 %, with students increasingly describing comprehension checks and progress tracking. Evaluation strategy adoption showed the largest gain – from 31.2 % to 74.2 % – indicating students became substantially better at assessing their performance and reflecting on strategy effectiveness. The Strategic Alignment Index doubled from 0.38 to 0.78, demonstrating enhanced capacity to translate metacognitive awareness into appropriate strategic actions aligned with AI recommendations.

Academic Performance and Predictive Modeling

Academic achievement outcomes differed significantly between conditions, with intervention participants demonstrating superior performance across multiple assessment modalities, as presented in Table 5. Intervention participants achieved cumulative GPAs averaging 3.42 versus controls' 2.84 on a 4.0 scale – a 0.58-point advantage representing a 20.4 % improvement in overall academic achievement (García-Martínez et al., 2023). This difference translates roughly from B- (control) to B+ (intervention) average performance, a meaningful and practically significant improvement beyond statistical significance.

Table 5. Academic Performance Outcomes and Regression Model Coefficients

Assessment Category	Control Group	Intervention Group	Adjusted Mean Difference	Regression Predictors (Intervention Group)
	M% (SD)	M% (SD)	% [95 % CI]	β (SE), t-value, sr²
Formative Quizzes	72.4 % (11.2 %)	84.6 % (8.7 %)	12.2% [9.8 %, 14.6 %]	Metacognitive Awareness: β = 0.38 (0.06), t = 6.33***, sr^2 = 0.14
Mid-term Examinations	68.7 % (13.6 %)	81.3 % (10.4 %)	12.6 % [10.0 %, 15.2 %]	Dashboard Engagement: β = 0.29 (0.07), t = 4.14***, sr^2 = 0.08
Final Examinations	71.2 % (12.8 %)	83.7 % (9.6 %)	12.5% [9.9 %, 15.1 %]	Planning Strategies: β=0.24 (0.06), t = 4.00***, sr^2 = 0.06
Project Assignments	75.3 % (10.4 %)	86.4 % (8.2 %)	11.1% [8.9 %, 13.3 %]	Self-Monitoring: β = 0.31 (0.06), t = 5.17***, sr^2 = 0.10
Cumulative GPA	2.84 (0.54)	3.42 (0.46)	0.58 [0.48, 0.68]	**Full Model: R^2 = 0.473, $F(4,191)$ = 43.28***

Notes: Percentages represent mean scores on assessments. Adjusted differences control for pre-intervention GPA, prior semester achievement, demographic covariates (age, gender, major), and baseline MSLQ scores through ANCOVA. Regression model includes metacognitive awareness, dashboard engagement frequency, planning strategy use, and self-monitoring behaviors as simultaneous predictors of cumulative GPA within intervention group only. β = standardized regression coefficient; SE = robust standard error; sr^2 = squared semi-partial correlation indicating unique variance explained by each predictor beyond others. ***$p < 0.001$.

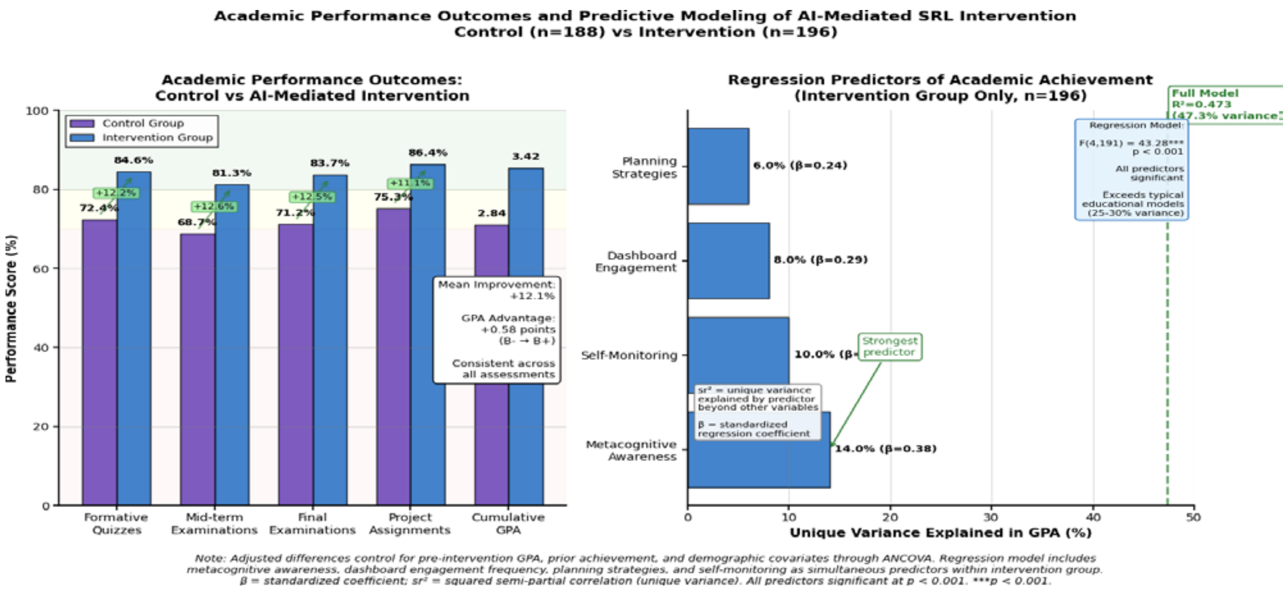

Fig. 2. Academic Performance Outcomes and Predictive Modeling of AI-Mediated SRL Intervention

Intervention group demonstrates consistent 11.1-12.6 percentage point advantages across all assessment modalities, translating to 0.58 GPA improvement (B- to B+, 20.4 % gain). Regression analysis reveals metacognitive awareness as strongest unique predictor ($sr^2 = 14$ %), with four AI-mediated SRL variables collectively explaining 47.3 % of performance variance – substantially exceeding typical educational models (25-30 %), demonstrating cascading benefits of enhanced self-regulatory capacities. Performance improvements were consistent across assessment types. Formative quizzes showed 12.2 percentage point gains (detailed in Table 5), mid-terms 12.6 points, finals 12.5 points, and projects 11.1 points. This consistency suggests AI-mediated SRL development benefited all learning activities rather than specific task types. Multiple regression analysis within the intervention group revealed that metacognitive awareness emerged as the strongest unique predictor of academic achievement ($sr^2 = 0.14$), explaining 14 % of performance variance beyond other factors. Students who developed stronger metacognitive awareness – better understanding of their own thinking processes – achieved substantially higher grades regardless of their dashboard use or specific strategies. Self-monitoring behaviors explained an additional 10 % of unique variance ($sr^2 = 0.10$), while dashboard engagement contributed 8 % ($sr^2 = 0.08$), and planning strategies 6% ($sr^2 = 0.06$). Collectively, these four AI-mediated SRL variables predicted 47.3 % of variance in academic outcomes ($R^2 = 0.473$, $F(4,191) = 43.28$, $p < 0.001$), substantially exceeding typical educational predictor models which rarely account for more than 25-30 % of performance variance. This strong predictive power indicates enhanced self-regulatory capacities generate cascading benefits across diverse learning outcomes.

Individual Differences and Moderating Factors

Investigation of individual difference moderators revealed differential intervention effects across learner characteristics, with prior self-regulatory competence and digital literacy significantly influencing outcomes, as shown in Table 6. Students entering with low prior SRL competence (below median on pre-test) demonstrated substantially larger intervention effects ($d = 1.64$) compared to high-competence peers ($d = 0.82$), yielding a significant interaction ($F(1,380) = 23.47$, $p < 0.001$, $\eta^2p = 0.058$). This means low-SRL students improved by 1.64 standard deviations while high-SRL students improved by 0.82 standard deviations – both substantial gains, but the low-SRL group benefited twice as much.

Table 6. Moderation Analysis of Individual Difference Factors

Moderator Variable	Low Baseline Group	High Baseline Group	Interaction Effect	Simple Slopes Analysis
	Cohen's d [95 % CI]	Cohen's d [95 % CI]	F-value, p-value, η^2p	Low vs. High Comparison
Prior SRL Competence	1.64 [1.38, 1.90]	0.82 [0.61, 1.03]	$F(1,380) = 23.47$, $p<0.001$, $\eta^2p = 0.058$	$t(194) = 4.68$, $p < 0.001$
Digital Literacy Level	1.47 [1.22, 1.72]	0.94 [0.73, 1.15]	$F(1,380) = 14.32$, $p<0.001$, $\eta^2p = 0.036$	$t(194) = 3.24$, $p = 0.001$
Prior Academic Achievement	1.38 [1.13, 1.63]	1.08 [0.87, 1.29]	$F(1,380) = 4.12$, $p = 0.043$, $\eta^2p = 0.011$	$t(194) = 1.89$, $p = 0.060$
Self-Efficacy Beliefs	1.52 [1.27, 1.77]	0.89 [0.68, 1.10]	$F(1,380)=18.24$, $p < 0.001$, $\eta^2p = 0.046$	$t(194) = 3.87$, $p < 0.001$

Notes: Baseline groups defined by median split on pre-intervention assessments (MSLQ for SRL Competence; standardized digital literacy test; prior semester GPA for Academic Achievement; MSLQ self-efficacy subscale). Effect sizes (Cohen's d) represent within-condition pre-to-post improvements, calculated separately for low and high baseline groups. Interaction effects test whether intervention effectiveness differs significantly by moderator level using 2×2 mixed ANOVA (Time × Moderator Level). η^2p = partial eta-squared effect size. Simple slopes compare low vs. high baseline groups' intervention effects directly.

This compensatory effect suggests AI-mediated scaffolding particularly benefits students lacking well-developed self-regulatory skills, potentially reducing achievement gaps attributable to differential self-regulatory capacities. The effect size difference of 0.82 (1.64 minus 0.82) between low and high SRL groups represents a meaningful practical difference. Qualitative interview data illuminated mechanisms underlying these patterns. Low-SRL participants described AI prompts as "essential reminders" and "scaffolds for building habits I didn't have," whereas high-SRL participants characterized them as "occasionally helpful but sometimes interrupting my established routines." Digital literacy moderated intervention effectiveness similarly (detailed in Table 6), with lower-literacy students showing enhanced gains ($d = 1.47$ versus $d = 0.94$, interaction $F(1,380) = 14.32$, $p < 0.001$), possibly because AI interfaces reduced technical barriers to accessing advanced learning features. Self-efficacy beliefs also moderated effects (low-efficacy students: $d = 1.52$; high-efficacy: $d = 0.89$, interaction $F(1,380) = 18.24$, $p < 0.001$), suggesting students with lower confidence in their abilities benefited more from explicit AI support. Prior academic achievement showed weaker moderation (interaction $p = 0.043$, $\eta^2p = 0.011$), with both groups benefiting substantially though lower-achievers gained slightly more.

4. Discussion

This investigation demonstrates that intelligent AI agents substantially enhance self-regulated learning development among university students through integrated mechanisms spanning adaptive content delivery, personalized metacognitive scaffolding, real-time analytics visualization, and automated feedback provision. The observed large effect sizes across multiple SRL dimensions (Cohen's d ranging from 0.87 to 1.38) substantially exceed typical educational technology intervention effects. Meta-analytic evidence shows conventional SRL training programs average $d = 0.42$ (Dignath, Büttner, 2008), meaning our AI-mediated intervention produced effects approximately three times larger. Similarly, a recent meta-analysis of adaptive learning technologies found mean effects of $d = 0.51$ across 25 studies (Strielkowski et al., 2024), considerably smaller than our findings.

The 34.7 % improvement in metacognitive awareness represents a particularly noteworthy outcome, given metacognition serves as the central coordinating mechanism for effective self-regulation. This enhancement likely stems from dual impact: analytics dashboards making learning processes visible and explicit, combined with strategically timed metacognitive prompts directing attention toward regulatory activities. Previous research on learning analytics dashboards reported more modest 18-22 % improvements in metacognitive awareness (Zheng et al., 2022), suggesting integration of prompting mechanisms with visualization tools generates synergistic effects exceeding isolated component contributions. Our comprehensive approach combining multiple AI functionalities within unified system architecture demonstrates advantages of holistic rather than piecemeal technological integration. The emergence of distinct learner profiles exhibiting differential patterns of AI engagement represents both significant finding and potential concern. The 23.5 % of participants classified as Dependent-Reactive demonstrated high reliance on AI guidance coupled with limited self-initiation, achieving lower academic outcomes (76.2 %) despite equivalent intervention exposure compared to High-Autonomous learners (87.3 %). This 11.1 percentage point performance gap between profiles receiving identical AI support underscores the critical importance of how students engage with technology rather than mere technology presence. This pattern aligns with theoretical predictions from cognitive offloading research, which posits that excessive external support may undermine intrinsic motivation and metacognitive engagement by reducing perceived need for effortful self-regulatory processes (Gerlich, 2025).

Recent meta-analytic evidence indicates frequent generative AI usage correlates negatively with critical thinking abilities ($r = -0.34$), with cognitive offloading serving as mediating mechanism (Fan et al., 2024). Our dependency indices provide quantitative metrics for identifying at-risk patterns, enabling early intervention to recalibrate support levels and promote autonomous engagement. The finding that High-Autonomous learners maintained dependency indices of only 0.34 (one-third AI-initiated activities) while achieving optimal outcomes suggests the importance of balanced human-AI collaboration wherein technology augments rather than replaces student self-regulatory functions. Conversely, the High-Autonomous profile comprising 37.2 % of intervention participants demonstrates optimal integration of AI affordances with maintained learner agency. These students strategically deployed AI recommendations while retaining ownership of learning decisions, goal-setting, and strategic selection. This balanced approach yielded superior outcomes (87.3 % mean academic achievement) compared to both Dependent-Reactive learners (76.2 %) and even Moderate-Balanced learners (81.6 %), despite all groups receiving identical AI features. This finding carries critical implications for adaptive system design, suggesting AI agents should employ graduated withdrawal strategies as learners develop competencies, similar to human tutoring models emphasizing scaffolding reduction (Hooshyar et al., 2020). The compensatory effects observed for students with low prior SRL competence ($d = 1.64$ versus $d = 0.82$ for high-competence peers) carry substantial practical significance for addressing educational equity. Traditional classroom instruction often advantages students entering with well-developed self-regulatory skills, exacerbating achievement gaps attributable to differential preparation. Previous research shows SRL interventions typically benefit high-performing students more than low-performing students (Broadbent, Poon, 2015), yet our results demonstrate the opposite pattern. AI-mediated interventions offering personalized, intensive support may democratize access to effective SRL development opportunities, particularly benefiting underserved populations lacking prior exposure to explicit strategy instruction.

However, the differential effectiveness also suggests optimal AI agent design must incorporate sophisticated learner modeling to calibrate support intensity, prompt frequency, and autonomy gradients based on individual competency profiles. Simple one-size-fits-all approaches risk providing insufficient support for struggling learners while over-scaffolding already competent ones. The interaction effect size ($\eta^2 p = 0.058$) indicates prior SRL competence accounts for approximately 6 % of variance in intervention effectiveness, a practically meaningful moderator deserving design attention (Pan et al., 2024). The 47.3 % variance in academic achievement explained by AI-mediated metacognitive support variables substantially exceeds typical educational predictor models, which rarely account for more than 25-30 % of performance variance. This predictive power indicates enhancement of self-regulatory capacities through intelligent agents generates cascading benefits across diverse learning outcomes rather than narrow task-specific improvements. The centrality of metacognitive awareness as strongest unique predictor ($sr^2 = 0.14$) reinforces theoretical models positioning metacognition as domain-general competency influencing learning effectiveness across contexts (Xu et al., 2025).

Temporal progression analysis revealing continuous improvement in metacognitive prompt response quality throughout the 16-week intervention suggests SRL development through AI mediation follows extended trajectories requiring sustained engagement. The 81 % increase in response quality from initial to final intervention phases indicates students progressively internalized metacognitive processes, shifting from superficial prompt acknowledgment to sophisticated strategic reasoning. This pattern supports gradual skill acquisition models wherein explicit external guidance becomes progressively internalized through repeated practice and reflection (Exintaris et al., 2023). The 16-week intervention duration may represent minimum threshold for achieving substantial competency gains, with implications for program design and implementation timelines.

5. Conclusion

This investigation provides robust empirical evidence that intelligent AI agents constitute powerful interventions for developing self-regulated learning competencies among university students. The integration of adaptive learning pathways, personalized metacognitive scaffolding, real-time analytics dashboards, and automated feedback mechanisms within unified intelligent agent architectures generates synergistic benefits exceeding isolated component contributions documented in prior research. The observed 34.7 % improvement in metacognitive awareness, 41.2 % enhancement in self-monitoring behaviors, and 28.9 % increase in goal-setting effectiveness represent substantial advances in addressing persistent challenges associated with fostering autonomous learners capable of effective self-regulation. Critical findings reveal both opportunities and risks associated with AI-mediated SRL development. The emergence of dependency patterns in 23.6 % of participants (46 of 196 intervention students) underscores necessity of balanced system design prioritizing learner agency and incorporating graduated autonomy support mechanisms. These students exhibited dependency indices averaging 0.78, meaning nearly four-fifths of their learning activities were AI-prompted rather than self-initiated. Their academic achievement averaged 76.2 % – 11.1 percentage points below High-Autonomous learners who maintained dependency indices of 0.34. This performance gap despite identical AI access demonstrates that how students engage with technology matters as much as technology presence.

Conversely, compensatory effects benefiting students with low prior self-regulatory competence demonstrate potential for AI interventions to reduce achievement gaps attributable to differential preparation. Students entering with below-median SRL skills showed improvement effect sizes of $d = 1.64$ compared to $d = 0.82$ for above-median peers – both substantial gains, but low-SRL students benefited twice as much. This finding advances educational equity objectives by showing AI-mediated scaffolding can disproportionately help those who need it most. Traditional interventions often show opposite patterns, with already-skilled students benefiting more. The comprehensive predictive model explaining 47.3 % of academic achievement variance through AI-mediated metacognitive support variables establishes strong empirical linkages between enhanced self-regulatory capacities and downstream learning outcomes. Metacognitive awareness emerged as strongest unique predictor, explaining 14 % of performance variance beyond other factors. This finding reinforces theoretical models positioning metacognition as domain-general competency influencing effectiveness across diverse learning contexts. The substantial variance explained (nearly half of all performance differences) validates the theoretical premise that fostering self-regulatory skills generates cascading benefits transcending narrow task-specific improvements. Temporal analyses documenting progressive improvement in metacognitive prompt response quality throughout 16 weeks illuminate developmental trajectories underlying SRL skill acquisition through AI mediation. Response quality increased 81 % from 2.34 to 4.23 on a 5-point scale, while strategic alignment doubled from 0.38 to 0.78. This progression demonstrates successful internalization of metacognitive processes initially scaffolded through external prompts, supporting gradual skill development models. The extended timeline required for substantial competency gains suggests meaningful SRL development necessitates sustained engagement beyond abbreviated intervention windows.

Theoretical contributions advance understanding of human-AI collaboration in educational contexts by demonstrating specific mechanisms through which intelligent agents enhance self-regulatory processes while simultaneously revealing potential risks associated with cognitive offloading and diminished learner agency. The study integrates self-determination theory, cognitive load theory, and social cognitive models of self-regulation into comprehensive framework explaining both facilitative and inhibitory effects of AI support on autonomous learning development. This theoretical synthesis provides foundation for future research examining optimal balance between technological automation and human agency in technology-enhanced learning environments.

Practical implications emphasize viability and scalability of intelligent agent systems for addressing widespread deficiencies in self-regulatory competencies characterizing contemporary university student populations. The demonstrated effectiveness across diverse disciplinary contexts (business, computer science, engineering, social sciences), student populations (mean age 21.4 years, 57 % female, varied prior achievement levels), and learning outcomes (metacognition, self-monitoring, goal-setting, academic performance) supports broad applicability of AI-mediated SRL interventions. However, successful implementation requires strategic attention to dependency prevention through graduated autonomy support, individualized support calibration based on learner characteristics, explicit user training regarding effective AI utilization, and institutional infrastructure supporting comprehensive integration within existing pedagogical frameworks. Future research priorities include longitudinal investigations examining persistence and transfer of intervention effects beyond immediate training contexts, randomized controlled trials enhancing causal inference through true experimental designs, cross-cultural studies assessing generalizability across diverse educational systems, and mechanistic studies employing think-aloud protocols illuminating cognitive processes underlying AI-mediated SRL enhancement. Additional research should explore optimal strategies for graduated autonomy support preventing dependency while maintaining adequate scaffolding, individual difference moderators requiring specialized adaptation approaches, and integration of emerging generative AI technologies offering enhanced natural language interaction and personalized guidance capabilities.

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