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Self-Regulated Learning with AI: A Comparative Analysis of General-Purpose and Task-Specific Platforms

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Abstract

Artificial intelligence (AI) offers opportunities for enhancing student self-regulated learning (SRL). This study investigates how two types of AI platforms—general-purpose AI (e.g., ChatGPT) and task-specific AI (e.g., EduGPT)—support SRL and satisfy students' psychological needs. Grounded in Zimmerman's SRL model and Self-Determination Theory (SDT), we examine the cognitive and motivational affordances provided by each AI type across multiple SRL phases. An experimental design involving 258 undergraduate students was implemented over an eight-week period. Participants were divided into three groups: general-purpose AI, task-specific AI, and control group. MANOVA results revealed that general-purpose AI tools primarily supported higher levels of autonomy and encouraged SRL skills such as goal setting, metacognitive reflection, and independent problem-solving. In contrast, task-specific AI tools were more effective in fostering competence and relatedness by providing structured guidance, timely feedback, and opportunities for social interaction, thereby enhancing effort regulation and social support. Thematic analysis further demonstrated distinct patterns in SRL strategies, with general-purpose AI promoting flexible self-directed learning, while task-specific AI provided scaffolding that encouraged incremental skill-building and collaboration. These findings underscore the complementary roles of the two AI tools in educational contexts, suggesting that a hybrid approach may optimize SRL.

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Introduction

The rapid integration of artificial intelligence (AI) in education has revolutionized the way students engage with instructional content (Chiu, & Rospigliosi, 2025). AI-powered tools hold the potential to personalize learning experiences, offering real-time feedback and scaffolding that can significantly enhance self-regulated learning (SRL) processes. Self-regulated students actively manage their learning through goal setting, progress monitoring, and strategy adjustments, essential for academic success (Zimmerman, 2008). Given the increasing demand for scalable, technology-enhanced educational systems, understanding how AI can effectively support SRL is critical.

The current literature has explored the broad impacts of AI on SRL, noting how AI systems can support various phases of learning by providing adaptive feedback and fostering metacognitive skills (Darvishi et al., 2024). The systems aid students in setting goals, planning learning strategies, and performing the strategies, and evaluating their learning. However, much of the existing research has treated AI as a uniform construct, with limited distinction between general-purpose AI systems, such as ChatGPT, and task-specific AI tools designed for particular educational tasks, such as EduGPT, intelligent tutoring systems for mathematics or language-specific writing assistants like Grammarly. This distinction is crucial, as the affordances provided by each AI type can vary significantly. General-purpose AI tools are designed to support a wide range of learning activities, offering broad, flexible guidance. In contrast, task-specific AI systems are tailored for specific educational tasks, providing more detailed and context-specific feedback (Triguero et al., 2024).

Despite the theoretical potential of both general-purpose and task-specific AI systems, little is known about how each type differentially supports SRL and addresses students' psychological needs. This gap in the literature presents a critical opportunity to examine the unique contributions of each AI type to SRL, particularly in how they foster students' cognitive and motivational affordances. Research suggests that students' psychological needs, as identified by Self-Determination Theory (SDT), such as autonomy, competence, and relatedness, play a vital role in promoting intrinsic motivation and effective self-regulation (Deci & Ryan, 2000). For example, students can request solutions for their problems from AI (autonomy), get specific feedback from AI (competence), as well as, find the response from AI personalized and relevant (relatedness) (Chiu, 2024; Li et al., 2025). Yet, it remains unclear how well general-purpose and task-specific AI systems can satisfy these needs within AI-enhanced learning environments. This study aims to fill this gap by investigating how general-purpose and task-specific AI systems support SRL and satisfy students' psychological needs. By addressing this, we aim to provide insights into the design of AI systems that optimize cognitive and motivational affordances in educational settings, ultimately advancing the understanding of AI's role in supporting SRL.

Literature Review

General-Purpose AI and Task-Specific AI

This type of AI is designed to perform a wide range of tasks across various domains (Triguero et al., 2024). General-purpose AI, such as ChatGPT and Deepseek, is versatile and adaptable, capable of learning and improving over time. Task-specific AI is specialized for a particular task or set of tasks, for example, intelligent tutorial systems for mathematics, speaking and writing assessment (language), codeGPT (coding), and is optimized for efficiency and accuracy in its designated function but lacks the flexibility to perform unrelated tasks. General-purpose AI has a broad scope, while task-specific AI is narrow and focused. General-purpose AI is flexible and can adapt to various tasks, whereas task-specific AI is rigid and specialized. General-purpose AI continuously learns and evolves, while task-specific AI is often pre-trained for specific tasks. Overall, general-purpose AI and task-specific AI may have an impact on SRL and SDT needs satisfaction.

The Role of AI in Supporting SRL

SRL plays a fundamental role in educational contexts, as it encompasses students' abilities to take control of their learning processes through goal setting, progress monitoring, and strategic adjustments (Zimmerman, 2008). SRL has gained increasing attention with the rise of AI in education, where AI tools are seen as valuable assets that can assist students in effectively managing their learning paths (Jin et al., 2023; Lim et al., 2023). AI systems can support three phrases of SRL – forethought, performance and self-evaluation – by providing tailored guidance and personalized feedback (Lim et al., 2023). During the phrase of forethought: AI systems help students set goals and plan strategies by analyzing their past performance and suggesting effective study methods (Chiu, 2024; Xia et al., 2023). During performance: AI systems provide real-time support, answering questions, offering explanations, and keeping students engaged (Chiu, 2024; Xia et al., 2023). During self-evaluation: AI systems assist in reflecting on progress by providing insights and feedback on completed tasks, helping students identify strengths and areas for improvement (Chiu, 2024; Xia et al., 2023). Overall, AI systems have the potential to enhance students' metacognitive abilities by scaffolding tasks and helping them track their learning progress (Khotimah & Mariono, 2024).

The integration of AI in education is particularly promising in terms of its ability to deliver real-time interventions and adaptive support (Chiu, 2024). AI systems can prompt students to set goals, monitor their task completion, and evaluate their performance, effectively fostering the SRL process (Chiu, 2024). However, despite the benefits of AI systems for SRL, much of the research has focused on AI as a general concept, without distinguishing between the varying capacities of different types of AI systems. Specifically, while some AI tools provide broad support applicable across various learning disciplines (general-purpose AI), others are designed to address specific tasks with more targeted feedback (task-specific AI) (Russell, 2021; Triguero et al., 2024).

This distinction between general-purpose AI and task-specific AI is crucial because the type of feedback and guidance provided can significantly influence students' SRL processes. General-purpose AI tools typically offer broad functionalities, supporting skills like time management and organization across different subjects (Triguero et al., 2024). These systems can help students maintain a high-level overview of their tasks but may lack the depth required for fostering more context-specific learning strategies. On the other hand, task-specific AI systems are designed to focus on narrow tasks, such as writing or problem-solving, providing highly tailored guidance that enhances students' ability to engage in strategic planning, self-efficacy (forethought), learning process monitoring (performance), and evaluation (self-reflection) (Darvishi et al., 2024).

Given the growing reliance on AI in education, there is a pressing need to examine how these different types of AI systems support SRL processes. Most studies have explored the broad impacts of AI on SRL, but few have conducted direct comparisons between general-purpose and task-specific AI systems. This lack of distinction represents a significant gap in literature and highlights the importance of understanding the specific ways in which different AI tools can facilitate SRL in educational settings.

AI and Psychological Needs

In addition to supporting SRL, AI systems can also play a crucial role in addressing students' psychological needs, particularly those identified in SDT—autonomy, competence, and relatedness (Deci & Ryan, 2000). These three needs are essential for intrinsic motivation, which drives students to engage more deeply in learning activities (Deci & Ryan, 2015). AI tools, by providing personalized feedback and adaptive learning pathways, have the potential to support these psychological needs in educational environments (Xia et al., 2023).

Research suggests that autonomy is supported when students have the freedom to make decisions about their learning paths, such as choosing tasks or strategies that align with their interests and abilities (Papamitsiou & Economides, 2019). Competence is fostered when students receive feedback that helps them understand their progress and develop their skills, while relatedness is enhanced when students feel connected to the learning process through supportive feedback and interactions with learning tools (Dai et al., 2024; Malecka & Boud, 2023).

Autonomy is supported as AI systems provide personalized learning experiences, allowing individuals to make choices and control their learning paths (Chiu, 2024; Lee et al., 2023). Competence is supported through adaptive feedback and tailored challenges that match the learner's skill level, promoting a sense of mastery (Chiu, 2024; Lee et al., 2023). Relatedness is supported by AI systems' ability to facilitate collaboration and communication (Chiu, 2024; Lee et al., 2023). By addressing these needs, AI creates an environment that motivates and engages learners, driving intrinsic motivation and fostering a deeper commitment to learning.

However, the ability of AI systems to fulfill these needs likely varies based on the type of AI being employed. General-purpose AI tools are often effective in providing broad, flexible support, offering students guidance that can be applied across a wide range of tasks (Triguero et al., 2024). These tools can provide students with flexible and broad-ranging support, helping them navigate diverse tasks. On the other hand, task-specific AI systems are inherently better equipped to meet students' psychological needs by providing detailed and adaptive feedback (Darvishi et al., 2024). These systems are designed to support students in making informed decisions about their learning strategies, which enhances autonomy by giving them greater control over their learning pathways (Lee et al., 2023). Additionally, task-specific AI tools offer actionable insights that directly address students' performance, thereby fostering competence by helping them build confidence in their abilities (Adorni et al., 2023).

While several studies have acknowledged the role of AI in supporting autonomy, competence, and relatedness, the question of how different types of AI systems achieve this support remains largely unanswered. Addressing this gap is critical for advancing our understanding of how AI can be optimized to meet students' psychological needs and foster intrinsic motivation in educational settings.

The Present Study

Research Questions

While there is a growing body of research comparing the impacts of AI systems on SRL and motivation, most studies have focused on the benefits of AI tools in a general sense without differentiating between task-specific and general-purpose systems. Qiao and Zhao (2023) found that AI systems can improve metacognitive processes and self-regulation but did not explore the distinct differences between AI types. Additionally, existing studies emphasize the importance of targeted feedback but fail to address how general-purpose systems may fall short in comparison to task-specific tools. This lack of direct comparative research highlights a significant gap: there is limited understanding of how general-purpose and task-specific AI systems differentially support SRL skills and satisfy psychological needs. To address these gaps, the present study is guided by three research questions that reflect the core issues identified in the literature:

RQ1: Are there differences in how well general-purpose and task-specific AI systems support SRL skills?
RQ2: Are there differences in how well general-purpose and task-specific AI systems support autonomy, competence, and relatedness satisfaction?
RQ3: How do the two AI systems support SRL skills and SDT needs (autonomy, competence, and relatedness)?

Hence, as we discussed in 2.1 and 2.2, we expect there are differences between general-purpose and task-specific AI systems in supporting SRL skills (RQ1) and SDT needs satisfaction (RQ2).

Participants

The participants were 258 first-year undergraduate students enrolled in College English course at a university in Shenzhen China. Purposeful sampling was applied to recruit the participants to ensure a diverse academic background in terms of their majors. The participants ranged in the age range from 18 to 22 years, with the majority being 20 years old (29.8%). Ninety of them were male (34.9%) and 168 were female (65.1%).The participants were randomly assigned to one of three intervention groups: (i) general-purpose (n = 91, 35.3%), task-specific (n = 88, 34.1%), and (iii) control (n = 79, 30.6%). We assigned the numbers 1, 2, 3, 1, and so on to the course list for the group. Prior to the intervention, the participants completed a baseline survey assessing their familiarity with SRL strategies, English proficiency, and prior exposure to AI tools in educational contexts. The survey confirmed that none of the participants had prior experience with the AI tools used in this study, ensuring no prior bias. Additionally, no significant differences were found between groups in terms of academic achievement and SRL capacity ($p > 0.05$).

To ensure ethical compliance, all participants provided informed consent and were made fully aware of the study's purpose and procedures. The study was conducted over the intervention period, during which participants interacted with their assigned tools as part of their regular coursework. Data confidentiality was maintained throughout the study. Participants were assigned unique identification codes, and all data were anonymized. The study protocol was approved by the Institutional Review Board of the university and adhered to established ethical guidelines.

Research Design and Procedure

This study used three intervention groups to answer the research questions: general-purpose, task-specific, and control group (see Figure 1). Three instructors taught the three groups. During the eight-week intervention, the three groups engaged in the same project-based learning tasks. Each week students had a 2-hour face-to-face lesson. These tasks, focusing on three topics—traveling abroad, selling, and preparing for a job interview—included conversational exercises and writing assignments. Students need to complete the three projects. To ensure consistent implementation across groups, instructors were trained in the use of the AI tools before the study began, and met every two weeks to discuss their teaching. The three groups had the same learning goals, schedule, content, and activities.

Before doing projects, the students get familiar with the three main SRL phrases: forethought, performance, and self-evaluation; see Table 1 and Table 2. Table 1 shows the suggested student learning activities with generative AI tools; Table 2 discusses how each activity supports the three phases of SRL. And the three needs of SDT. These activities were suggested by the corresponding author's (2024) Delphi study. In other words, the students got ideas of how to use their AI tools to support their SRL.

In each lesson, the instructors gave a 15-minute lecture to their students about the three topics. The teachers served as facilitators to assist students in finishing the assignments following the lecture. They answered students' questions related to the topics. General-purpose and task-specific groups use their own corresponding AI tools to support their SRL process. The students had their freedom to use AI tools to support their project completion. Following the intervention, we randomly selected ten students from each intervention group to participate in the interviews.

- General-purpose group engaged general-purpose AI platforms – ERNIE (developed by Baidu), and Doubao (developed by ByteDance) in SRL. These two platforms, ChatGPT alternative, were developed using large language models. They are both generic and not designed for a specific education purpose. Students may need extra effort to understand the feedback and comments given by the platforms in SRL process.
- Task-specific group engaged AI tools specifically designed for language education –iWrite and FiF in SRL. iWrite provided detailed feedback on written tasks, offering students insights on grammar, sentence construction, and style. This specific feedback allowed students to improve the technical quality of their writing. FiF could help students enhance their spoken English by providing real-time feedback on pronunciation, fluency, and intonation. FiF's targeted feedback enabled students to refine their speaking skills, focusing on natural delivery and professional communication.

- The control group adopted a business-as-usual approach. i.e., participated in conventional learning activities without AI support.

Activity logs showed all the students use AI tools in each lesson. We collect all the data, including self-reports on SRL behaviors, psychological needs satisfaction, course performance outcomes, and interviews at the end of the intervention.

Table 1. Learning Activities Using AI Tools

	Learning Activities	**Descriptions**
#1	search information	allow students to get a more complex source of information than information from a search engine. An AI tool is viewed as a smart search engine.
#2	get examples	allow students to get more examples for a topic or problem.
#3	check their answers	ask students to compare their answers or solutions to those provided by an AI tool.
#4	generate review questions to check for their understanding	ask students to generate review questions for them to answer in order to check for their understanding.
#5	create new problems for practice	ask students to create problems, such as mathematics questions or reading passages, for drilling and practice.
#6	create challenging problems	ask students to create challenging problems to amplify their achievements and keep them humble.
#7	get insight into complex problems	encourage students to get a new or different perspective on solving complex problems.
#8	ask ideas for their improvement	ask students to improve their work, e.g., other ways of solving mathematics problems, as well as writing edits and suggestions.
#9	make lists or outlines	allow students to make a list for solving a problem or generate an outline for a report or an article.
#10	summarize their own work	ask students to summarize their work and check whether the summary is good.
#11	ask for definitions	ask students to get definitions of a term at various levels.
#12	generate questions for discussions	get ideas from generating questions for classroom discussions when needed.
#13	generate questions for essays	get ideas from generating questions for writing essays when needed.
#14	get feedback for their work	ask students to get feedback on their original work.
#15	practice peer feedback	ask students to practice peer feedback by giving comments on the outputs from AI tool.
#16	prepare for tough conversations	encourage students to have tough conversations with an AI tool.
#17	visualize a problem	encourage students to visualize text-based content.
#18	anticipate an AI tool's outputs	anticipate the response you would expect from an AI tool.
#19	grade an AI tool's outputs	encourage students to grade outputs from an AI tool.
#20	debate with an AI tool	encourage students to debate a topic with an AI tool.

Table 2. AI Learning Activities, SDT Needs, and SRL Phases

	Learning Activities	Autonomy	Competence	Relatedness	Forethought	Performance	Self-reflection
#1	search information	X			X		
#2	get examples	X			X		
#3	check their answers		X				X
#4	generate review questions to check for their understanding		X				X
#5	create new problems for practice		X				X
#6	create challenging problems		X				X
#7	get insight into complex problems	X				X	
#8	ask ideas for their improvement		X				X
#9	make lists or outlines	X			X		
#10	summarize their own work			X		X	
#11	ask for definitions		X		X		
#12	generate questions for discussions	X				X	
#13	generate questions for essays	X				X	
#14	get feedback for their work		X				X
#15	practice peer feedback		X			X	
#16	prepare for tough conversations		X			X	
#17	visualize a problem			X		X	
#18	anticipate an AI tool’s outputs		X				X
#19	grade an AI tool’s outputs		X				X
#20	debate with an AI tool	X				X	

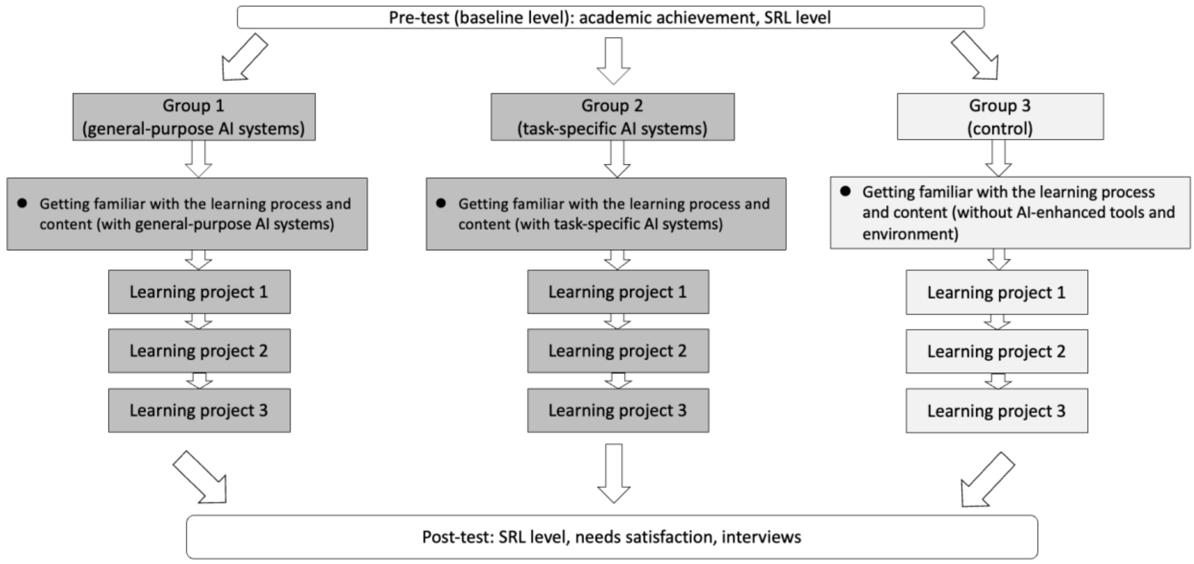

Figure 1. Research Design

Instruments and Measures

The SRL-O questionnaire, which has been widely validated in previous research for assessing SRL behaviors across diverse educational contexts (Broadbent et al., 2023). We used 7-point Likert scale of this questionnaire to measure students' SRL. Its reliability and construct validity have been consistently supported in many contexts including university student language learning (Broadbent et al., 2023; Tarchi et al., 2024). In this study, the instrument demonstrated strong internal consistency for measuring SRL, with Cronbach's alpha values ranging from 0.81 to 0.87, indicating acceptable to good reliability within the present sample.

We used 7-point Likert the Basic Psychological Need Satisfaction and Need Frustration Scale (BPNSFS) to measure students' autonomy, competence, and relatedness satisfaction in their learning environment (Chen et al., 2015). This instrument has demonstrated strong psychometric properties, as evidenced by previous studies including university language learning (Chen et al., 2015; Chevrier & Lannegrand, 2021; Frielink et al., 2019; Liga et al., 2020). In the current study, Cronbach's alpha values for the constructs ranged from 0.81 to 0.89, indicating acceptable to excellent reliability.

The semi-structured interview guide was developed based on prior research on SRL and SDT (Deci & Ryan, 2015; Zimmerman, 2008). The interview guide was designed to explore how the two AI systems facilitated students' SRL and addressed their psychological needs for satisfaction. The interview guide was pilot tested with two participants, and minor adjustments were made to clarify certain questions.

Data Analysis

The quantitative data collected were analyzed using IBM SPSS Statistics (Version 29.0.2). To analyze differences among the three groups, multivariate analysis of variance (MANOVA) was performed on each of the dependent variables. Where significant differences emerged, Bonferroni post-hoc tests were applied to pinpoint specific group differences. Additionally, effect sizes were calculated to quantify the magnitude of the observed differences across groups.

The qualitative data were analyzed using thematic analysis, following Braun and Clarke (2006) six-step approach. First, interview transcripts were read and re-read to familiarize the researchers with the data. Second, initial codes were generated based on participants' descriptions of how they used the two AI systems to support their SRL skills and psychological needs. Third, similar codes were grouped into broader themes. Fourth, these themes were reviewed and refined to ensure they accurately represented the data. Fifth, detailed definitions were assigned to each theme, and finally, the results were written, with relevant quotes included to illustrate key points.

Results

Descriptive Statistics

Table 3 presents the descriptive statistics for the primary study variables. The mean scores across SRL phases showed moderate levels of self-regulation among participants. For example, academic self-efficacy had a mean score of 4.92 (SD = 1.05), while metacognition and intrinsic motivation showed similar means of 4.83 (SD = 1.05) and 4.85 (SD = 1.04), respectively.

Table 3. Descriptive Analysis

Constructs	Mean	SD	Variance	Skewness	Kurtosis
Academic Self-Efficacy	4.92	1.05	1.11	-0.08	0.32
Metacognition	4.83	1.05	1.10	0.12	0.06
Intrinsic Motivation	4.85	1.04	1.08	0.06	0.30
Negative Achievement Emotions (reversed)	4.27	1.10	1.21	-0.54	1.04
Extrinsic Motivation	3.77	1.03	1.06	0.34	0.14
Goal Setting and Time Management	4.61	1.12	1.25	0.04	0.08
Study Environment	4.78	1.11	1.24	0.08	0.02
Effort Regulation	4.82	0.98	0.96	0.02	0.24
Social Support	4.87	1.04	1.09	0.02	0.07
Task Strategies	4.40	0.84	0.71	0.19	0.40
Autonomy Satisfaction	3.93	0.58	0.33	0.36	-0.40
Competence Satisfaction	4.02	0.57	0.33	0.29	-0.45
Relatedness Satisfaction	3.93	0.59	0.35	0.26	-0.47

The psychological needs constructs indicate moderate levels of satisfaction, with mean scores ranging from 3.93 to 4.02, standard deviations between 0.57 and 0.59. Skewness and kurtosis values for all variables were within acceptable ranges, indicating that the data were approximately normally distributed (Field, 2018).

AI Intervention and SRL (RQ1)

The MANOVA results indicate significant group differences across all SRL constructs (see Table 4). Specifically, Group 1 consistently shows higher means for constructs related to academic self-efficacy, metacognition, intrinsic motivation, and study environment compared to Groups 2 and 3. Conversely, Group 2 demonstrates the highest scores in effort regulation, goal setting, time management, and social support, suggesting distinct patterns of SRL support among the groups.

Table 4. Group Descriptive Statistics of SRL Constructs

	Group	Mean	Std. Deviation
ASEf	1	6.04	0.57
	2	4.83	0.26
	3	3.74	0.57
MeCog	1	5.99	0.56
	2	4.62	0.32
	3	3.72	0.52
InM	1	5.99	0.56
	2	4.66	0.31
	3	3.73	0.53
NAE	1	5.01	0.97
	2	4.13	0.88
	3	3.57	0.94
ExM	1	3.66	0.29
	2	4.88	0.68
	3	2.67	0.49
GSTM	1	4.44	0.35
	2	5.85	0.60
	3	3.42	0.63
SE	1	5.97	0.63
	2	4.60	0.37
	3	3.60	0.60
ER	1	4.75	0.30
	2	5.88	0.55
	3	3.72	0.49
SS	1	4.72	0.29
	2	6.05	0.52
	3	3.73	0.54
TS	1	5.30	0.52
	2	4.28	0.27
	3	3.49	0.39

Between-subjects effects confirm that Group 1 generally outperformed the others in constructs such as academic self-efficacy and metacognition, while Group 2 excelled in constructs like effort regulation and social support (see Table 5).

Table 5. MANOVA Summary

Constructs	F-value	Effect Size (η^2)
Academic Self-Efficacy	472.95*	0.79
Metacognition	489.13*	0.79
Intrinsic Motivation	481.03*	0.79
Negative Achievement Emotions	51.59*	0.29
Extrinsic Motivation	390.98*	0.75
Goal Setting and Time Management	434.18*	0.77
Study Environment	410.28*	0.76
Effort Regulation	462.51*	0.78
Social Support	540.68*	0.81
Task Strategies	426.63*	0.77

Note: *. The mean difference is significant at the .05 level.

Post hoc comparisons using the Bonferroni test revealed significant differences between the groups across all SRL constructs (see Table 6). Group 1 outperformed Group 2 in academic self-efficacy, metacognition, intrinsic motivation, negative achievement emotions, study environment, and task strategies. These results suggest that Group 1 demonstrated stronger SRL capabilities in areas that involve personal motivation, strategic planning, and a supportive learning environment. Conversely, Group 2 outperformed Group 1 in effort regulation, extrinsic motivation, goal setting and time management, and social support. This indicates that Group 2 was more effective in managing efforts, setting goals, and leveraging external motivators and social support in their learning process.

Table 6. Post-Hoc Analysis of SRL

Dimension	Group Comparison	Mean Difference	95% CI Lower	95% CI Upper
Academic Self-Efficacy	Group 1 vs Group 2	1.21*	1.03	1.38
	Group1 vs Group 3	2.30*	2.12	2.48
	Group 2 vs Group 3	1.09*	0.91	1.27
Metacognition	Group 1 vs Group 2	1.37*	1.20	1.55
	Group1 vs Group 3	2.27*	2.09	2.45
	Group 2 vs Group 3	0.90*	0.72	1.08
Intrinsic Motivation	Group 1 vs Group 2	1.33*	1.15	1.50
	Group1 vs Group 3	2.25*	2.08	2.43
	Group 2 vs Group 3	0.93*	0.75	1.11
Negative Achievement Emotions	Group 1 vs Group 2	0.88*	0.54	1.22
	Group1 vs Group 3	1.44*	1.09	1.78
	Group 2 vs Group 3	0.56*	0.21	0.91

Dimension	Group Comparison	Mean Difference	95% CI Lower	95% CI Upper
Extrinsic Motivation	Group 1 vs Group 2	-1.22*	-1.41	-1.04
	Group1 vs Group 3	0.99*	0.80	1.18
	Group 2 vs Group 3	2.21*	2.02	2.40
Goal Setting and Time Management	Group 1 vs Group 2	-1.40*	-1.60	-1.21
	Group1 vs Group 3	1.02*	0.82	1.22
	Group 2 vs Group 3	2.42*	2.22	2.62
Study Environment	Group 1 vs Group 2	1.37*	1.18	1.57
	Group1 vs Group 3	2.38*	2.17	2.58
	Group 2 vs Group 3	1.00*	0.80	1.21
Effort Regulation	Group 1 vs Group 2	-1.13*	-1.29	-0.96
	Group1 vs Group 3	1.02*	0.85	1.19
	Group 2 vs Group 3	2.15*	1.98	2.32
Social Support	Group 1 vs Group 2	-1.33*	-1.49	-1.16
	Group1 vs Group 3	0.99*	0.82	1.16
	Group 2 vs Group 3	2.32*	2.15	2.49
Task Strategies	Group 1 vs Group 2	1.02*	0.87	1.16
	Group1 vs Group 3	1.81*	1.66	1.96
	Group 2 vs Group 3	0.79*	0.64	0.95

Note: Group 1: general-purpose; Group 2: task-specific; Group 3 control group

*. The mean difference is significant at the .05 level.

AI Interventions and Needs Satisfaction (RQ2)

A MANOVA was conducted to examine the effect of AI type on students' satisfaction of the three basic psychological needs: autonomy, competence, and relatedness. Descriptive statistics for the dependent variables across the three groups are provided in Table 7.

Table 7. Group Descriptive Statistics of Needs Satisfaction

	Group	**Mean**	**Std. Deviation**
Autonomy	1	4.52	0.43
	2	3.89	0.13
	3	3.30	0.25
Competence	1	3.96	0.09
	2	4.63	0.42
	3	3.41	0.29
Relatedness	1	3.94	0.11
	2	4.52	0.44
	3	3.25	0.25

The between-subjects effects analysis revealed significant group differences in autonomy, competence, and relatedness satisfaction. For autonomy, the group effect was significant, F (2, 255) =355.87, p<.001, η^2=.736, indicating a large effect size and substantial variance explained by group membership. Similarly, for competence, the analysis yielded a significant group effect, F (2,255) =353.09, p<.001, η^2=.735, also reflecting a large effect. Lastly, the effect of group on relatedness was significant, F (2,255) =374.94, p<.001, η^2=.746.

The post-hoc analysis confirms that there are statistically significant differences between all group comparisons across the three dimensions (see Table 8). Group 1 consistently showed higher autonomy scores compared to Group 2 and Group 3, while Group 2 reported significantly higher competence and relatedness scores than the other groups.

Table 8. Post-Hoc Analysis of Needs Satisfaction

Dimension	Group Comparison	Mean Difference	95% CI Lower	95% CI Upper
Autonomy	Group 1 vs Group 2	1.21*	1.03	1.38
	Group1 vs Group 3	2.30*	2.12	2.48
	Group 2 vs Group 3	1.09*	0.91	1.27
Competence	Group 1 vs Group 2	-1.33*	-1.49	-1.16
	Group1 vs Group 3	0.99*	0.82	1.16
	Group 2 vs Group 3	2.32*	2.15	2.49
Relatedness	Group 1 vs Group 2	1.02*	0.87	1.16
	Group1 vs Group 3	1.81*	1.66	1.96
	Group 2 vs Group 3	0.79*	0.64	0.95

Note: Group 1: general-purpose; Group 2: task-specific; Group 3 control group

*. The mean difference is significant at the .05 level.

Thematic Analysis of Interview (RQ3)

The thematic analysis of the interviews revealed distinct patterns in SRL skills and psychological needs satisfaction between users of general-purpose and task-specific AI tools (see Table 9). In terms of SRL skills, participants using general-purpose AI tools demonstrated greater independence in planning and goal setting, often setting their own objectives and determining the focus of their learning. They engaged in frequent self-monitoring and strategy adjustment, with reflections on the need to modify approaches when faced with challenges. Additionally, these participants highlighted the opportunity for independent problem-solving, describing the experience as both challenging and rewarding, as they navigated learning tasks without detailed guidance.

In contrast, users of task-specific AI tools reported a more structured approach to SRL, facilitated by the tool’s design. These participants described how the tools supported goal setting and time management through task segmentation and progress tracking, which helped them maintain focus. Self-monitoring was also more systematic, as task-specific tools offered predefined steps that simplified effort regulation. Participants using these tools reflected on their learning more through structured feedback, allowing them to pinpoint strengths and areas for improvement.

With respect to psychological needs satisfaction, general-purpose AI users reported a high degree of autonomy, appreciating the freedom to explore topics at their discretion. However, their competence satisfaction was occasionally tempered by uncertainty regarding the accuracy of AI-provided information. Task-specific AI users, conversely, felt a greater sense of competence due to the step-by-step guidance and feedback that affirmed their progress. They also experienced relatedness when the tool allowed for feedback from instructors and visibility into peers' progress, fostering a sense of social connection.

Table 9. Summary of Thematic Analysis

Theme	**Sub-theme**	**General-Purpose AI**	**Task-Specific AI**
SRL Skills	Planning and Goal Setting	*"I had to decide where to start and what information to focus on."* *"Using the AI tool such as DouBao, I need to ask very specifically what I wanted to learn to get the satisfactory answers from the tools."*	*"Tools like iWrite and FiF set small goals within the task, so I was clear about the purpose of each practice."* *"I liked that it tracked my progress and kept me on schedule with timed tasks. It kept me focused and less likely to get distracted."*
	Self-Monitoring and Adjusting Strategies	*"Sometimes I had to change my strategy if I felt I wasn't understanding the content well."* *"The tool made me think about different ways to approach the problem since there wasn't just one solution."*	*"The way it broke down tasks made it easier to manage my effort, especially when I started feeling overwhelmed."*
	Reflection on Learning	*"I realized that I was learning more effectively when I approached the tool with targeted and specific questions."* *"Using this tool made me more aware of my own strengths and weaknesses."*	*"The tool's feedback made me think about how I was doing with each task, and I could see where I needed to improve."*
	Independent Problem-Solving	*"I enjoyed figuring things out on my own rather than being told exactly what to do."* *"It was satisfying to explore a new*	*"The tool provided understandable steps, but I still needed to practice more to make sure I master each part."*

Theme	Sub-theme	General-Purpose AI	Task-Specific AI
		topic, even though it was challenging at times because I was not sure about the answers."	
Psychological Needs	Autonomy	*"I liked that I could explore topics in my own way without any strict instructions. For example, DouBao will provide some possible questions for inquiring. This feature helps me expand my knowledge scope."* *"The AI gave me the freedom to choose what to focus on, which made learning more interesting."*	*"It was helpful to have a clear path, but most of the time I can't ask the tools some personalized questions."*
	Competence	*"There were moments when I wasn't sure if I was doing it right because I'm not very sure the answers provided are correct or not."*	*"FiF and iWrite guided me step-by-step, and I could see my progress, such as by gaining more badges."*
	Relatedness	*"I mostly worked alone with DouBao."*	*"I can receive feedback or reminders from my teacher, as well as seeing the progress and achievement from my peers on FiF."*

Discussion

Are There Differences in How Well General-Purpose and Task-Specific AI Systems Support SRL Skills? (RQ1)

The main findings of this study indicate that general-purpose AI tools support certain SRL skills more effectively than task-specific AI tools, while the reverse holds true for other SRL dimensions (see Figure 2). Specifically, participants using general-purpose AI tools reported higher levels of academic self-efficacy, metacognition, intrinsic motivation, and a supportive study environment. This aligns with the open-ended and flexible nature of general-purpose AI, which enables students to independently set their own goals, engage in reflective learning practices, and explore content autonomously. In contrast, participants using task-specific AI tools scored highest in effort regulation, goal setting and time management, and social support, reflecting the structured guidance these tools provide, which assists students in managing their time and energy more efficiently. General-purpose AI tools seem to offer a flexible platform for students to engage in these higher-order SRL skills. The flexibility provided by general-purpose AI aligns well with existing literature on open-ended learning environments, which has shown that autonomy in selecting learning paths fosters intrinsic motivation and metacognitive skills (Núñez & León, 2016). Conversely, the structured guidance of task-specific AI tools aligns with studies showing that scaffolding and targeted feedback can enhance students' effort regulation and time management, particularly for novice students or those needing directed support (Munshi et al., 2023).

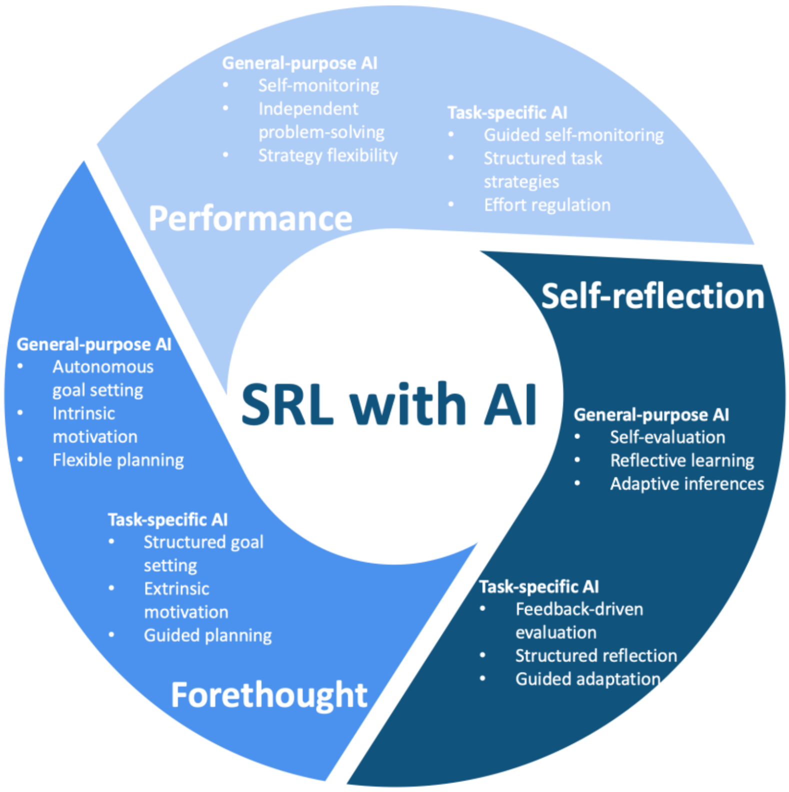

Figure 2. AI Tools' Affordances in SRL

However, while general-purpose AI supports independence, it may leave some students uncertain about whether they are progressing effectively, potentially impacting self-efficacy. This finding reflects the balance between autonomy and guidance found in SRL literature (Papamitsiou & Economides, 2019), where too much freedom without clear guidance can lead to uncertainty. In contrast, task-specific AI, by providing structured feedback and explicit goals, builds students' confidence in managing specific tasks, which may account for the higher scores in effort regulation and social support. These results are comparable to research by Liu et al. (2024), which suggests that structured support systems are effective for students who benefit from step-by-step guidance.

Another minor finding suggests that learning with AI tools significantly supports the three phases of SRL more effectively than teachers, which is supported by some review studies (e.g., Li et al., 2024; Weng et al., 2024). AI tools are more personalized than teachers. Teachers also may not be able to give timely feedback to students, while AI tools can do it. This continuous support and adaptability make AI tools more effective than teacher support in SRL, fostering a more engaging and productive SRL environment (Li et al., 2024; Weng et al., 2024).

Are There Differences in How Well General-Purpose and Task-Specific AI Systems Support Autonomy, Competence, and Relatedness Satisfaction? (RQ2)

The main findings from our study reveal distinct patterns in how general-purpose and task-specific AI tools support students' basic psychological needs (see Figure 3). Specifically, general-purpose AI tools were shown to provide significantly higher levels of autonomy satisfaction, as these tools offer students more freedom to explore topics, set personal learning paths, and make decisions independent of rigid guidance. In contrast, task-specific AI tools were more effective in supporting competence and relatedness. Task-specific tools offered structured support and feedback that allowed students to monitor their progress and build confidence, thus fostering a sense of competence. Additionally, these tools provided mechanisms for social interaction and feedback (e.g., through teacher feedback or peer comparisons), enhancing students' sense of relatedness.

Figure 3. How AI Tools Support SDT Needs

The higher autonomy scores for general-purpose AI tools align with the inherent flexibility and student-centered nature of these tools. The freedom to choose learning paths and determine the depth of exploration promotes a sense of agency and control, essential components of autonomy. These findings are consistent with prior studies suggesting that environments allowing students greater control and choice tend to enhance autonomy satisfaction (Admiraal et al., 2024). However, this increased autonomy may come at the cost of certainty and guidance, as some students might feel overwhelmed without explicit direction, which could impact their perceived competence if they lack confidence in their learning decisions. This nuance underscores the complex relationship between autonomy and other psychological needs, suggesting that while autonomy is beneficial, an optimal balance of guidance may still be necessary for students who are developing SRL skills.

In contrast, task-specific AI tools led to higher competence satisfaction. These tools often provide step-by-step instructions, clear goals, and targeted feedback, which support students in achieving specific tasks and building their skills incrementally. This structured guidance aligns with findings from studies on scaffolding (van de Pol et al., 2010), which highlight that directed support can help students experience "mastery moments," reinforcing their belief in their capabilities. Our results resonate with similar findings by (Shin & Song, 2022), where task-specific support in computer-based learning were shown to improve students' self-efficacy by enhancing task comprehension and reducing cognitive load. Task-specific tools, therefore, may be especially beneficial for students who require clear benchmarks and feedback to feel competent, highlighting their role in supporting students' development through structured and reliable feedback mechanisms.

With respect to relatedness, task-specific AI tools facilitated a higher sense of connectedness than general-purpose AI tools. This was achieved through integrated features that allowed students to interact with instructors or compare their progress with peers, fostering a social learning environment even within an AI-driven setting. Task-specific AI tools appear to replicate some aspects of collaborative learning by providing avenues for interaction or feedback, which could help students feel a sense of community and shared experience. These results are also consistent with recent studies on technology-enhanced learning and relatedness (Weng et al., 2024), indicating that tools that include social elements contribute to a stronger sense of belonging and can be especially impactful in online and technology-mediated learning environments.

Another minor finding suggests that learning with AI tools significantly satisfies all three SDT needs—autonomy, competence, and relatedness—more effectively than teachers, which is supported by some review studies (e.g., Heung & Chiu, 2025; Li et al., 2024). This needs satisfaction could be attributed to the fact that AI tools offer a higher degree of personalization and adaptability compared to conventional teacher support. By tailoring learning experiences to individual student needs and preferences (Chiu, 2024), AI tools can provide more targeted support and feedback, thereby fostering a more engaging and effective learning environment (Chiu, 2024).

How Do the Two AI Systems Support SRL Skills and SDT Needs (Autonomy, Competence, and Relatedness)? (RQ3)

The thematic analysis of interviews provided deeper insights into how general-purpose and task-specific AI tools uniquely support SRL skills and fulfill students' psychological needs. General-purpose AI tools appeared to foster SRL skills such as planning, goal setting, self-monitoring, and independent problem-solving by offering students flexibility and autonomy in managing their learning processes. However, they were less effective in fostering relatedness and sometimes led to uncertainty regarding competence, as students had to navigate content independently. This aligns with prior studies indicating that autonomy-supportive environments encourage students to take control of their learning trajectories, resulting in more strategic goal setting and task management (Duchatelet & Donche, 2019). In this study, participants using general-purpose AI tools frequently described setting personal goals, reflecting on their learning strategies, and engaging in independent problem-solving. However, the open-ended nature of general-purpose tools may introduce uncertainty in competence for some students, particularly those who are less experienced with SRL. These tools may inadvertently place a cognitive load on students, requiring them to manage both the content and the tool itself, which can sometimes hinder confidence.

In contrast, task-specific AI tools provided a more structured learning environment that enhanced effort regulation, provided clear guidance on goal setting, and offered feedback on task performance. The structured design provides explicit guidance and feedback, which has been shown to enhance students' feelings of competence (Hammond & Moore, 2018). This structured support aligns with Vygotsky's zone of proximal development, which suggests that scaffolding can help students achieve tasks they might not complete independently (Vygotsky, 1978). Task-specific AI users in our study reported feeling more competent as the tools provided clear benchmarks and feedback on performance. The structured nature of these tools also facilitated relatedness by allowing for social comparisons, feedback from instructors, or even collaborative elements, fostering a sense of belonging and connection.

The contrasting impacts of general-purpose and task-specific AI tools on SRL skills and psychological needs reflect broader findings in AI-enhanced learning research. Our results resonate with studies that have shown the value of autonomy in promoting deep learning and engagement but also highlight the potential trade-offs when autonomy is not balanced with guidance (Núñez & León, 2019). AI's potential to personalize support allows for adaptive adjustments based on student progress, an area where general-purpose AI tools could be further enhanced to provide targeted scaffolding.

These findings offer valuable insights into the effective integration of AI tools in educational settings. Educators should consider aligning AI tool selection with students' SRL development levels and psychological needs. General-purpose AI tools, which support autonomy and independent problem-solving, may be more suitable for students who already possess strong self-regulation skills and can manage the open-ended nature of such tools. For younger or less experienced students, task-specific AI tools can provide the necessary guidance, enhancing their competence and relatedness through structured feedback and social interaction.

Conclusion

Implications

The findings from this study provide several key implications for the integration of AI technologies in educational settings, particularly regarding the alignment of AI tool types with students' SRL skills and psychological needs. First, our results suggest that general-purpose and task-specific AI tools serve complementary roles in supporting students' SRL skills and psychological needs. General-purpose AI tools, by offering high levels of autonomy and flexibility, are well-suited for fostering advanced SRL skills such as independent goal setting, metacognitive reflection, and problem-solving. As such, these tools may be most effective for students who possess well-developed self-regulation skills or are engaged in exploratory, open-ended learning tasks. Educators and instructional designers should consider integrating general-purpose AI tools in contexts that prioritize creativity, self-direction, and the exploration of complex, multi-faceted problems. Conversely, task-specific AI tools excel in providing structured guidance, clear feedback, and social interaction features, making them highly effective for building students' competence and relatedness. These tools are particularly valuable for novice students or those in need of scaffolding, as they offer structured pathways and opportunities for social engagement through instructor feedback or peer comparisons. The structured support provided by task-specific AI tools aligns well with learning environments that emphasize step-by-step skill development, mastery of foundational content, and goal-oriented tasks. Therefore, task-specific AI should be prioritized in instructional designs aimed at fostering initial competence and community, such as foundational courses or learning modules where students are developing core skills and knowledge.

The differential impacts of these AI tool types underscore the need for a nuanced approach to AI integration in education, where AI selection and deployment are tailored to specific learning objectives and student profiles. The results call for ongoing innovation and research in hybrid AI solutions that combine the autonomy-supportive elements of general-purpose AI with the structured guidance of task-specific tools. By allowing adaptive shifts between autonomy and support based on students' evolving needs, AI tools could provide a more personalized, responsive, and effective learning experience. Such advancements hold the potential to not only enhance SRL and motivation but also democratize high-quality, AI-supported learning opportunities, bridging gaps for diverse students across educational contexts.

Limitations

This research was limited by its focus on language learning tools, which may affect the generalizability of findings to other educational domains. Future research should explore the application of task-specific AI in broader subjects. Additionally, the reliance on self-reported data introduces potential biases, and longitudinal studies are recommended to assess the long-term impact of AI systems on SRL and motivation.

References

Admiraal, W., Post, L., Kester, L., Louws, M., & Lockhorst, D. (2024). Learning labs in a secondary school in the Netherlands: Effects of teachers' autonomy support on student learning motivation and achievement. *Educational Studies*, *50*(5), 939-956. https://doi.org/10.1080/03055698.2021.2023473

Adorni, G., Mangili, F., Piatti, A., Bonesana, C., & Antonucci, A. (2023). Rubric-based student modelling via noisy gates bayesian networks for computational thinking skills assessment. *Journal of Communications Software and Systems*, *19*(1), 52-64. https://doi.org/10.24138/JCOMSS-2022-0169

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology*, *3*(2), 77-101. https://doi.org/10.1191/1478088706qp063oa

Broadbent, J., Panadero, E., Lodge, J. M., & Fuller-Tyszkiewicz, M. (2023). The self-regulation for learning online (SRL-O) questionnaire. *Metacognition and Learning*, *18*(1), 135-163. https://doi.org/10.1007/s11409-022-09319-6

Chen, B., Vansteenkiste, M., Beyers, W., Boone, L., Deci, E. L., Van der Kaap-Deeder, J., Duriez, B., Lens, W., Matos, L., Mouratidis, A., Ryan, R. M., Sheldon, K. M., Soenens, B., Van Petegem, S., & Verstuyf, J. (2015). Basic psychological need satisfaction, need frustration, and need strength across four cultures. *Motivation and Emotion*, *39*(2), 216-236.

Chevrier, B., & Lannegrand, L. (2021). Basic Psychological Need Satisfaction and Frustration Scale (BPNSFS): Validation of the French adaptation within freshman year students. *Psychologie Francaise*, *66*(3), 289-301. https://doi.org/10.1016/j.psfr.2020.09.005

Chiu, T. K. F. (2024). A classification tool to foster self-regulated learning with generative artificial intelligence by applying self-determination theory: a case of ChatGPT. *Educational Technology Research and Development*, *72*(4), 2401-2416. https://doi.org/10.1007/s11423-024-10366-w

Chiu, T. K. F., & Rospigliosi, P. 'asher.' (2025). Encouraging human-AI collaboration in interactive learning environments. Interactive Learning Environments, 33(2), 921–924. https://doi.org/10.1080/10494820.2025.2471199

Dai, W., Tsai, Y. S., Gašević, D., & Chen, G. (2024). Designing relational feedback: a rapid review and qualitative synthesis. *Assessment and Evaluation in Higher Education*. https://doi.org/10.1080/02602938.2024.2361166

Darvishi, A., Khosravi, H., Sadiq, S., Gašević, D., & Siemens, G. (2024). Impact of AI assistance on student agency. *Computers and Education*, *210*, 104967. https://doi.org/10.1016/j.compedu.2023.104967

Deci, E. L., & Ryan, R. M. (2000). The "what" and "why" of goal pursuits: Human needs and the self-determination of behavior. *Psychological Inquiry*, *11*(4), 227-268. https://doi.org/10.1207/S15327965PLI1104_01

Deci, E. L., & Ryan, R. M. (2015). Self-Determination Theory. In *International Encyclopedia of the Social & Behavioral Sciences: Second Edition* (pp. 486-491). https://doi.org/10.1016/B978-0-08-097086-8.26036-4

Duchatelet, D., & Donche, V. (2019). Fostering self-efficacy and self-regulation in higher education: a matter of autonomy support or academic motivation? *Higher Education Research and Development*, *38*(4), 733-747. https://doi.org/10.1080/07294360.2019.1581143

Field, A. (2018). GLM 5: Mixed designs. *Discovering Statistics Using IBM SPSS 5th Edition. SAGE Publications*, 703-734.

Frielink, N., Schuengel, C., & Embregts, P. J. C. M. (2019). Psychometric properties of the basic psychological need satisfaction and frustration scale - intellectual disability (BPNSFS-ID). *European Journal of Psychological Assessment*, *35*(1), 37-45. https://doi.org/10.1027/1015-5759/a000366

Hammond, L. S., & Moore, W. M. (2018). Teachers taking up explicit instruction: The impact of a professional development model including directive instructional coaching. *Australian Journal of Teacher Education*, *43*(7), 110-133. https://doi.org/10.14221/ajte.2018v43n7.7

Heung, Y. M. E., & Chiu, T. K. F. (2025). How ChatGPT impacts student engagement from a systematic review and meta-analysis study. *Computers and Education: Artificial Intelligence, 8*, 100361. https://doi.org/10.1016/j.caeai.2025.100361

Jin, S. H., Im, K., Yoo, M., Roll, I., & Seo, K. (2023). Supporting students' self-regulated learning in online learning using artificial intelligence applications. *International Journal of Educational Technology in Higher Education*, *20*(1), Article 37. https://doi.org/10.1186/s41239-023-00406-5

Khotimah, K., & Mariono, A. (2024). Enhancing Metacognitive and Creativity Skills through AI-Driven Meta-Learning Strategies. *International Journal of Interactive Mobile Technologies*, *18*(5), 18-31. https://doi.org/10.3991/ijim.v18i05.47705

Lee, D., Kim, H. H., & Sung, S. H. (2023). Development research on an AI English learning support system to facilitate student-generated-context-based learning. *Educational Technology Research and Development*, *71*(2), 629-666. https://doi.org/10.1007/s11423-022-10172-2

Li, Y., Zhou, X., & Chiu, T. K. F. (2024). Systematics review on artificial intelligence chatbots and ChatGPT for language learning and research from self-determination theory (SDT): what are the roles of teachers?. *Interactive Learning Environments*. https://doi.org/10.1080/10494820.2024.2400090

Liga, F., Ingoglia, S., Cuzzocrea, F., Inguglia, C., Costa, S., Lo Coco, A., & Larcan, R. (2020). The Basic Psychological Need Satisfaction and Frustration Scale: Construct and predictive validity in the italian context. *Journal of Personality Assessment*, *102*(1), 102-112. https://doi.org/10.1080/00223891.2018.1504053

Lim, L., Bannert, M., van der Graaf, J., Singh, S., Fan, Y., Surendrannair, S., Rakovic, M., Molenaar, I., Moore, J., & Gašević, D. (2023). Effects of real-time analytics-based personalized scaffolds on students' self-regulated learning. *Computers in Human Behavior*, *139*, 107547. https://doi.org/10.1016/j.chb.2022.107547

Liu, H., Zhang, Y., & Jia, J. (2024). The Design of Guiding and Adaptive Prompts for Intelligent Tutoring Systems and Its Effect on Students' Mathematics Learning. *IEEE Transactions on Learning Technologies*, *17*, 1379-1389. https://doi.org/10.1109/TLT.2024.3382000

Malecka, B., & Boud, D. (2023). Fostering student motivation and engagement with feedback through ipsative processes. *Teaching in Higher Education*, *28*(7), 1761-1776. https://doi.org/10.1080/13562517.2021.1928061

Munshi, A., Biswas, G., Baker, R., Ocumpaugh, J., Hutt, S., & Paquette, L. (2023). Analysing adaptive scaffolds that help students develop self-regulated learning behaviours. *Journal of Computer Assisted Learning*, *39*(2), 351-368. https://doi.org/10.1111/jcal.12761

Núñez, J. L., & León, J. (2016). The mediating effect of intrinsic motivation to learn on the relationship between student's autonomy support and vitality and deep learning. *Spanish Journal of Psychology*, *19*, e42. https://doi.org/10.1017/sjp.2016.43

Núñez, J. L., & León, J. (2019). Determinants of classroom engagement: a prospective test based on self-determination theory. *Teachers and Teaching: Theory and Practice*, *25*(2), 147-159. https://doi.org/10.1080/13540602.2018.1542297

Papamitsiou, Z., & Economides, A. A. (2019). Exploring autonomous learning capacity from a self-regulated learning perspective using learning analytics. *British Journal of Educational Technology*, *50*(6), 3138-3155. https://doi.org/10.1111/bjet.12747

Qiao, H., & Zhao, A. (2023). Artificial intelligence-based language learning: illuminating the impact on speaking skills and self-regulation in Chinese EFL context. *Frontiers in Psychology*, *14*, 1255594. https://doi.org/10.3389/fpsyg.2023.1255594

Russell, S. (2021). The history and future of AI. *Oxford Review of Economic Policy*, *37*(3), 509-520. https://doi.org/10.1093/oxrep/grab013

Shin, Y., & Song, D. (2022). The effects of self-regulated learning support on students' task performance and cognitive load in computer programing. *Journal of Educational Computing Research*, *60*(6), 1490-1513. https://doi.org/10.1177/07356331211052632

Tarchi, C., Vettori, G., Lodge, J. M., & Broadbent, J. (2024). Validation study of the Italian version of the Self-regulation for Learning Online (SRL-O) questionnaire in university students. *BPA Applied Psychology Bulletin*, *82*(299), 49-61.

Triguero, I., Molina, D., Poyatos, J., Del Ser, J., & Herrera, F. (2024). General Purpose Artificial Intelligence Systems (GPAIS): Properties, definition, taxonomy, societal implications and responsible governance. *Information Fusion*, *103*, Article 102135. https://doi.org/10.1016/j.inffus.2023.102135

van de Pol, J., Volman, M., & Beishuizen, J. (2010). Scaffolding in teacher-student interaction: A decade of research. *Educational Psychology Review*, *22*(3), 271-296. https://doi.org/10.1007/s10648-010-9127-6

Vygotsky, L. S. (1978). *Mind in society: The development of higher psychological processes* (Vol. 86). Harvard university press.

Weng, X., Xia, Q., Ahmad, Z., & Chiu, T. K. F. (2024). Personality traits for self-regulated learning with generative artificial intelligence: The case of ChatGPT. *Computers and Education: Artificial Intelligence, 7*, 100315.

https://doi.org/10.1016/j.caeai.2024.100315

Xia, Q., Chiu, T. K. F., & Chai, C. S. (2023). The moderating effects of gender and need satisfaction on self-regulated learning through Artificial Intelligence (AI). *Education and Information Technologies*, *28*(7), 8691-8713. https://doi.org/10.1007/s10639-022-11547-x

Zimmerman, B. J. (2008). Investigating self-regulation and motivation: Historical background, methodological developments, and future prospects. *American Educational Research Journal*, *45*(1), 166-183. https://doi.org/10.3102/0002831207312909