Investigating the Impact of Chatbot Integration on Self-Regulated Learning and Academic Success

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Abstract

As educational technology increasingly shifts from a supportive to an intrinsic component of pedagogy, chatbots have emerged as vital tools for providing personalized, asynchronous learning support. This study investigated the relationship between chatbot usage frequency, academic performance, and Self-Regulated Learning (SRL) proficiency among university students. Using a modified version of the SRL-SRS scale, we assessed the cognitive, metacognitive, and motivational dimensions of 69 participants. While the correlation between chatbot interaction and final exam grades was positive, it did not reach statistical significance, potentially due to a small reporting subsample. However, a significant positive correlation was found between usage frequency and SRL scores in second-year students, suggesting that academic maturity may moderate how digital assistants influence self-regulation. Furthermore, a significant link was confirmed between the diversity of digital tool usage and overall SRL levels. These findings highlight the potential of chatbots to bolster self-regulatory practices, though future research with larger cohorts and generative AI-driven chatbots is required to further validate these effects.

Keywords

Self-Regulated Learning, Educational Technology, Chatbots, Student Performance

1. Introduction

The digitalization of education keeps advancing and so does the use of respective educational technology (EdTech) [1]. Chatbots, in particular, are gaining increased importance as they offer personalized learning experiences and enhanced pedagogical support [2]. To this end, research indicates that the use of chatbots allows students to synchronize their learning pace with individual needs [3], and that it fosters higher engagement and interest compared to other, more traditional pedagogical methods [4]. Chatbot integration is furthermore associated with improvements in critical thinking, motivation, and overall academic achievement (ibid.). And, while students often encounter obstacles in monitoring their learning, defining goals, and managing time [5], these burdens may be mitigated by chatbot systems that assist in structuring and planning study processes [6]. Looking at it from a learning theory point of view, we may therefore argue that chatbot use can enhance engagement across various learning domains and potentially lead to superior academic outcomes [7]. To test this assumption, our goal was to investigate potential correlations between students' chatbot usage frequency and their exam performance as well as their Self-Regulated Learning (SRL) proficiency. Additionally, we wanted to collected data on students' affinity for technology and their openness toward Artificial Intelligence (AI) tools in relation to self-regulatory practices so as to explore whether individual technology preferences may affect these assumed relationships. Guidance was found in the following research question:

To what extent is the use of chatbot technology in education related to self-regulated learning and the learning success of students?

Following, we outline the relevant definitions and theoretical constructs underpinning this study. Section 3 then describes our methodological approach and Section 4 elaborates on our results. Finally, Section 5 concludes, highlights limitations of our work and proposes future research directions.

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2. Definitions and Theoretical Constructs

The continuous evolution of EdTech has been an accelerator for the education market [8], where today the role of technology is increasingly shifting from a mere support tool to an intrinsic component of modern pedagogy [1]. Chatbot systems have gained particular prominence in this field. These systems act as *digital tutors* or *learning assistants*, utilizing conversational functions to convey knowledge and provide a channel for reflection [7]. Recent advancements in natural language processing further enable them to provide justifications and additional content in a highly communicative manner [9]. However, the impact of such tools still depends heavily on user engagement [10].

2.1. Educational Technology (EdTech)

EdTech refers to the use of digital technology, consisting of hardware and software, that mediates and promotes educational activities [3]. It involves the managing of learning content, the tracking of progress, and the addressing of technological needs to develop human capabilities [11]. Factors such as cost-efficiency and ease of access have contributed to foster its current popularity. Beyond hardware like tablets and smartphones [1], it is particularly interactive learning management systems that play a vital role in that they provide web-based platforms which aim to increase student engagement [12]. To this end, the integration of AI-based tools has become especially significant, as those are used to adapt content to a learner's pace and provide immediate feedback, thereby enhancing overall learning productivity [13]. Respective, applications range from mobile language applications such as *Duolingo*[1] to asynchronous online quizzes and digital storytelling tools [10, 12]. In a sense, these modern EdTech tools therefore function as *adaptive systems* that tailor the learning process to individual student expectations [14]. By analyzing usage data, they, e.g., identify students struggling with materials and customize the experience accordingly [15]. Furthermore, they may assist in administrative tasks, such as automated grading, which may increase the efficiency of instructors [14, 13].

2.2. Chatbot in Education

Chatbots in education serve as interactive AI-based tools that foster student motivation and facilitate knowledge acquisition [16]. They have been perceived as useful assistants in higher education across engineering, science, and language courses [17]. Both students and educators report positive attitudes toward these systems, provided they are easy to use [18]. As so-called *learning assistants* chatbots help reduce stress by automating tasks and assisting in academic research and decision-making [9, 2]. They also enable learners to visualize and analyze information, promoting the development of new skills [19]. More advanced chatbot systems furthermore monitor student goals and adapt support throughout the learning process, integrating cognitive and metacognitive prompts [20]. They may also offer personalization features, which aim to ensure student needs throughout an entire study phase [21]. Finally, chatbots also offer more utilitarian features, such as automated notifications for exams and attendance records [22]. Over-reliance on chatbots, however, may diminish students' critical thinking and problem-solving skills [23]. There is also the risk of so-called *hallucinations*, where unverified, biased, or inaccurate information is presented as fact, potentially leading to poorer academic outcomes for students lacking prior subject knowledge [24].

2.3. Self-Regulated Learning (SRL)

SRL is the ability of learners to understand and control their learning environment through cognitive strategies, metacognitive processing, and motivational factors [25]. It is a cyclical process involving goal setting, planning, and reflection [26, 27]. Students proficient in SRL typically achieve higher grades and experience less stress [28]. Successful SRL requires the integration of three pillars [29]:

[1]Online: https://en.duolingo.com/ [accessed: 26 March 2026]

- Cognition: Adequate strategies for critical thinking and problem-solving to acquire knowledge [27].
- Metacognition: The regulation of cognition, including reflection and help-seeking behaviors to solve tasks [30, 31].
- Motivation: Driven by self-efficacy and the belief in one's ability to succeed, which sustains effort and engagement [30].

Reflection and self-monitoring in the metacognitive layer are essential for performance, while self-efficacy in the motivation layer significantly impacts academic success [26]. High levels of self-regulation lead to increased effort and superior learning results [32].

2.3.1. Planning and Chatbot Integration in SRL

Planning involves developing a methodology to achieve set goals by aligning abilities with requirements [33]. This process must occur continuously before and after learning phases to ensure efficiency [34]. Students who structure their learning through planning are more likely to meet course objectives and value feedback [35]. Chatbots support this by allowing students to learn at their own pace, thereby increasing self-efficacy [18, 17]. By providing external regulation, they help students maintain metacognitive monitoring, which can be difficult to sustain independently [7]. Automated reminders further stimulate motivation [36], while personalized feedback enhances self-monitoring and helps students apply cognitive strategies like summarization across diverse subjects [37, 16].

2.3.2. Self-Efficacy and Reflection in SRL

Self-efficacy refers to the belief in one's capacity to organize actions to reach specific goals [38]. According to social-cognitive theory, high self-efficacy encourages students to tackle difficult tasks rather than avoid them (ibid.). Here research indicates that increased chatbot usage correlates with positive shifts in student self-efficacy and consequently their overall learning effectiveness [39, 40].

Reflection, a meta-cognitive process, involves monitoring background cognitive functions [41]. This is categorized into prospective (pre-task), concurrent (during task), and retrospective (post-task) assessments [42]. Students use reflection to identify weaknesses and adjust their behavior, often aided by external feedback from human (or digital) instructors [43, 44].

2.4. Technological Affinity and Openness

Technological affinity posits the active interaction with technology viewed as a personal resource where high levels of interaction correlate with increased tool trust [45]. Conversely, a lack of openness often stems from a preference for human empathy and emotional intelligence, which chatbot technology currently lacks [46]. Implementation must account for such preferences in order to be successful [47].

3. Methodology

We used an experimental study targeting first and second year information system students participating in a class on software engineering principles. They were provided with a rule-based chatbot asking multiple-choice questions to help them prepare for their final exam. Upon exam completion they were then asked to complete a survey that collected data on their self-regulated learning proficiencies and their overall technological affinity and AI openness. Participation was voluntary and approved by the school's ethics committee.

3.1. Measures

The study utilized several key metrics to assess student engagement and performance, centered around a modified version of Toering et al.'s Self-Regulated Learning Self-Report Scale (SRL-SRS) [48, 49]. That

is, to improve survey efficiency, we condensed the original 50-item instrument into a 25-item scale focusing on three specific subscales and standardized the response format to a consistent four-point Likert scale. Beyond self-reporting, behavioral data was gathered by tracking the frequency of chatbot interactions during exam preparation and documenting the total number of digital tools students used for planning. Additionally, we evaluated participants' technological readiness and acceptance of AI, while academic outcomes were measured via voluntary submissions of exam grades and overall GPA.

3.2. Hypotheses

Based on existing literature, the following hypotheses were formulated and subsequently tested:

- H1: Higher chatbot usage correlates with better exam grades [50, 16, 9].
- H2: Increased interaction with a chatbot is connected to higher self-efficacy [40, 17].
- H3: Chatbot use encourages stronger reflection on learning processes [7, 50, 51].
- H4: Frequent chatbot interaction connects to more systematic cognitive planning [31, 16, 18].
- H5: Chatbot usage intensity correlates with overall SRL expression [20, 52, 50].
- H6: Higher SRL skills are positively connected with superior academic performance [26, 28, 30].
- H7: Greater openness toward AI tools correlates with higher technological affinity [45, 18].
- H8: Higher usage of digital tools correlates with stronger SRL levels [9, 17, 31].

3.3. Data Collection and Analysis

Chatbot interaction data was collected via a rule-based multiple-choice quiz application embedded into a *Matrix*[2] bot, which was available via dedicated *Element*[3] client applications (mobile or desktop apps) or through a standard internet browser. Self-reported data was collected via Microsoft Forms using a QR code distributed during lectures. Data analysis was conducted using *IBM SPSS Statistics*[4], where the primary statistical tests conducted included: (1) Spearman Rank Correlations to determine linear relationships between non-normally distributed variables; (2) Mann-Whitney U-Tests to compare usage frequency across different semesters or groups; and (3) ordinal regression analyses to analyze the relationship between chatbot usage and exam grades while controlling for a student's general GPA.

4. Results

Participation in the study started with 95 students (58 first year, 37 second year) of whom 69 stayed active until the time of the final exam. The gender distribution of the participants was largely balanced, with 53% identifying as male and 47% as female. The age of the respondents ranged from 19 to 30 years, with 22-year-olds representing the largest cohort ($n = 20$). Access to the chatbot was distributed between platforms, with 55% using the browser application and 45% utilizing the mobile application.

4.1. Hypotheses Evaluation

Before hypothesis testing, metric variables underwent Shapiro-Wilk and Kolmogorov-Smirnov tests to define their probability distributions. The Shapiro-Wilk test was prioritized due to its higher sensitivity for smaller samples. Results showed that the data for *Age* ($p < 0.001$), *Tool Usage* ($p < 0.001$), *Reflection Score* ($p = 0.004$), and *GPA* ($p = 0.027$) were non-normally distributed where as the data for *Self-efficacy* ($p = 0.424$), *Planning* ($p = 0.265$), and the overall *SRL* score ($p = 0.814$) were normally distributed. This prevalence of non-normal distributions across several key variables required us to use non-parametric procedures, specifically Spearman's Rank Correlation, for the subsequent analyses.

[2]Online: https://matrix.org/ [accessed: March 27 2026]
[3]Online: https://element.io/en [accessed: March 27 2026]
[4]Online: https://www.ibm.com/de-de/products/spss-statistics [accessed: March 27 2026]

4.1.1. H1: Usage Frequency and Exam Grades

The Spearman correlation yielded a moderate positive effect ($r = 0.257$), suggesting that higher usage frequency correlates with better grades. However, the result was not statistically significant ($p = 0.376$), likely due to the limited sample size (only n = 14 participants agreed to share their final grades with us). An ordinal regression with GPA as a control variable confirmed low explanatory power (*McFadden's* $R^2 = 0.161$) and non-significant impacts from usage frequency categories.

4.1.2. H2, H3, and H4: Usage Frequency and SRL Components

We investigated correlations between usage frequency and individual *Self-efficacy* (H2). Overall, a moderate positive yet non-significant effect was observed ($r = 0.159$; $p = 0.152$). Looking at a connection between usage frequency and *Reflection* (H3), the effect was also moderately positive ($r = 0.122$) but not significant ($p = 0.271$). Finally, focusing on *Planning* (H4), also a low positive but not significant correlation was found ($r = 0.176$; $p = 0.111$).

4.1.3. H5: Usage Frequency and Overall SRL

While the aggregate sample showed a non-significant correlation between usage frequency and *SRL* ($r = 0.212$, $p = 0.054$), a group-specific analysis revealed a significant result. For second-year students, a significant medium positive correlation was identified ($r = 0.365$, $p = 0.027$), indicating that higher chatbot usage in this group was associated with higher SRL scores. This suggests that academic maturity may influence how chatbot interaction relates to self-regulation.

4.1.4. H6: SRL and Academic Performance

A significant relationship was also confirmed between the overall SRL score and a student's GPA ($r = -0.286$, $p = 0.015$). Given that in our case lower numerical values represent better grades, this medium negative effect demonstrates that higher SRL proficiency is connected to superior academic performance.

4.1.5. H7 and H8: AI Openness, Technological Affinity and Tool Usage

The correlation between openness to AI tools and technological affinity was weakly positive ($r = 0.131$) yet not-significant ($p = 0.238$). However, a significant medium correlation was found between the number of digital tools used and the overall SRL score ($r = 0.286$, $p = 0.014$). This supports the hypothesis that students who integrate more digital resources into their studies exhibit higher levels of self-regulated learning.

4.2. Discussion

Literature suggests that chatbots with feedback functions can enhance learning gains and the application of SRL strategies [50]. However, risks such as over-dependence may impair independent problem-solving [6]. Looking at our data, the Spearman correlation for H1 was not significant ($p = 0.376$), and ordinal regression confirmed that neither GPA ($p = 0.071$) nor usage frequency significantly predicted exam grades. While surprising, these results are likely constrained by the small sample size ($n = 14$).

4.2.1. Psychological and Metacognitive Impacts (H2–H4)

While research indicates that AI interaction can bolster self-efficacy [40], there is a counter-risk that highly capable AI might lead students to undervalue their own skills [6]. Missing support for our H2 ($p = 0.152$) may suggest high baseline self-efficacy regardless of chatbot use. Similarly, despite theories that chatbot prompts encourage metacognitive reflection [36] and support cognitive strategies [50, 51], our hypotheses H3 ($p = 0.271$) and H4 ($p = 0.111$) were not supported. These unexpected outcomes might stem from imprecise survey item formulations or low measurement sensitivity.

4.2.2. Chatbots and Self-Regulated Learning (H5)

Digital tutors are theorized to provide individualized support that enhances SRL components [20]. While some warn that convenience may stifle critical thinking, others argue that chatbots can be designed to trigger active reflection [52]. For our complete sample, the correlation between usage and SRL was just short of significance ($p = 0.054$). However, looking at the second year students alone, we found a significant positive correlation ($p = 0.027$). The greater variance in this group's SRL scores and a more even distribution of usage frequency likely contributed to this finding, as higher standard deviations can influence significance outcomes in comparative testing [4]. Thus, the link between usage and SRL was at least partially confirmed by our study results.

4.2.3. Academic Success and Digital Integration (H6–H8)

Consistent with literature identifying SRL as a key predictor of success [30], also our H6 was confirmed ($p = 0.015$), showing that higher SRL skills correlate with superior grades [28]. Regarding technology, however, our H7 had to be rejected ($p = 0.238$), suggesting that technological affinity exists independently of specific openness toward AI. Finally, H8 confirmed a significant link between the diversity of digital tool usage and individual SRL levels ($p = 0.014$). This contradicts the notion that digital tools inherently undermine self-regulation [6], instead supporting the idea that they are vital for modern learners [13].

5. Conclusions, Limitations and Future Outlook

The primary objective of this research was to investigate the correlations between chatbot usage, self-regulated learning, and academic performance, specifically exam grades. The theoretical framework was constructed around Self-regulation Theory [25], which was operationalized through selected items from the standardized SRL-SRS scale by Toering et al. [48]. This approach allowed for the measurable assessment of students' SRL components planning, reflection, and self-efficacy within a digital learning environment. A central focus was placed on the relationship between chatbot interaction frequency and summative assessment outcomes. Despite employing both Spearman's rank correlation and ordinal regression with GPA as a control variable, the model failed to identify a statistically significant connection between usage frequency and final exam grades. While a latent trend suggested a potential link between prior academic standing (GPA) and exam performance, the data lacked sufficient power to be conclusive. Furthermore, the analysis explored the connection between usage frequency and the overall SRL score. While the aggregate correlation was non-significant, a segmented analysis revealed a significant positive relationship within a specific subgroup (second year students). This suggests that the impact of chatbot technology on self-regulation may be moderated by academic experience or curriculum integration.

5.1. Limitations

Several constraints temper the generalizability of the results and the interpretative scope of our findings. First, the usage phase and data collection period were relatively brief, precluding the observation of longitudinal effects such as the sustained development of SRL skills or the impact of iterative chatbot feature updates. Second, the study was restricted to specific student groups within a single degree program at one educational institution. This narrow focus limits the broader applicability of the findings to different disciplines or institutional cultures. Third, data collection relied heavily on voluntary participation, particularly regarding the disclosure of sensitive information like grades and GPA. Consequently, a self-selection bias may exist, as a significant number of potential candidates did not provide data. Fourth, the measurement of SRL components was based on student self-assessments. Such subjective metrics are inherently susceptible to social desirability bias or inaccurate self-perception. Furthermore, external variables such as individual learning preferences were not controlled for. Finally,

the degree to which the chatbot was authentically integrated into the students' daily learning routines may have been insufficient to trigger measurable shifts in cognitive or metacognitive behavior.

5.2. Outlook and Future Research

To advance our understanding of chatbot learning assistants larger participant cohorts are essential to provide the statistical power necessary for robust analysis, particularly regarding the correlation between usage and academic grades, which was hampered here by our small subsample (note: only 14 people shared their grades with us). Furthermore, we suggest to integrate more diverse degree programs and multiple geographic locations, which would allow for a more nuanced and differentiated analysis of how different academic environments interact with chatbots. Future investigations should also evolve to include more precisely selected SRL items and perhaps supplement self-reports with objective log data of student behavior. Finally, a logical step to progress this research would be to involve the deployment of more sophisticated, generative AI-based chatbots. Investigating how advanced natural language processing affects student engagement and regulatory processes will be a critical future frontier in educational technology.

Declaration on Generative AI

During the preparation of this work, the author(s) used Gemini 3 in order to: Translate, summarize and check grammar and spelling. After using these tool(s)/service(s), the author(s) reviewed and edited the content as needed and take(s) full responsibility for the publication's content.

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