

THE ROLE OF GENERATIVE ARTIFICIAL INTELLIGENCE IN FOSTERING SELF-REGULATED LEARNING STRATEGIES WITHIN DIGITAL HIGHER EDUCATION

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Abstract – *The rapid spread of generative artificial intelligence (GenAI) tools such as ChatGPT has created both opportunities and risks for self-regulated learning (SRL), a competence that largely determines student success in digital higher education. This article aims to synthesise current evidence on how GenAI influences students' SRL strategies and to identify the pedagogical conditions under which GenAI fosters rather than substitutes self-regulation. An integrative literature review was conducted on 18 peer-reviewed publications from 2023–2026, comprising nine empirical studies involving 1,394 university students, six systematic reviews and meta-analyses, and three conceptual design frameworks. The publications were coded deductively against Zimmerman's three-phase SRL model and analysed thematically. The results show that GenAI supports all three phases: goal setting and resource search in the forethought phase, problem-solving strategies and progress monitoring in the performance phase, and feedback and self-assessment in the self-reflection phase. However, gains in task performance did not consistently translate into knowledge gain, transfer or accurate self-evaluation, and several studies reported reduced mental effort, over-reliance and metacognitive laziness. Improvements in SRL processes were observed when GenAI use was combined with explicit metacognitive support or with reflective feedback based on learning analytics. The article proposes a conditional model in which GenAI acts as a regulation amplifier only when the learner retains metacognitive agency, and as a regulation substitute otherwise. Practical recommendations are formulated for universities, including those of Uzbekistan, concerning assignment design, AI literacy and teacher development. The findings can inform institutional policies on the responsible integration of GenAI into digital higher education.*

Keywords: *generative artificial intelligence, self-regulated learning, metacognition, ChatGPT, digital higher education, learner agency, cognitive offloading, AI-generated feedback, metacognitive scaffolding, AI literacy*

INTRODUCTION

Higher education is undergoing a profound digital transformation. Online and blended formats, learning management systems and data-driven services have become an integral part of everyday academic practice, giving students unprecedented flexibility in where, when and how they learn. This flexibility, however, comes at a price: in digital environments students themselves bear much of the responsibility for planning, monitoring and evaluating their learning. Self-regulated learning (SRL) – the cyclical process through which learners set goals, select and adapt strategies, monitor their progress and reflect on outcomes – has therefore become a key determinant of success in online higher education [7, 38]. Systematic evidence shows that time

management, metacognition, effort regulation and critical thinking are positively associated with academic achievement in online learning environments [7], and that prompts, feedback and other forms of SRL support can strengthen self-regulation in online courses and MOOCs [31].

Since the public release of ChatGPT in November 2022, generative artificial intelligence (GenAI) has entered universities at an unprecedented pace. Large language models can explain concepts, generate examples, provide instant feedback on drafts and engage students in dialogue at any time, which makes them potentially powerful learning partners [17, 34]. At the same time, the same tools are capable of completing many academic tasks on the student's behalf. Students themselves are aware of this duality: they value GenAI for personalised learning support, writing, brainstorming and research, but are concerned about the accuracy of its outputs, privacy, ethics and its impact on their personal development [8]. International organisations accordingly call for a human-centred approach to the use of GenAI in education and research [21].

The core scientific problem lies in the relationship between GenAI and self-regulation itself. On the one hand, GenAI can serve as an always-available scaffold for planning, monitoring and reflection. On the other hand, it invites cognitive offloading – the delegation of cognitive work to external tools [26] – and may thus weaken the very metacognitive processes on which SRL depends. Early experimental findings are contradictory: students working with ChatGPT often produce better task outputs without learning more [14], and unrestricted access to GenAI can even impair independent performance once the tool is withdrawn [4]. It therefore remains insufficiently understood which SRL phases GenAI actually supports, what risks it introduces and under what conditions it fosters rather than replaces students' self-regulation.

The problem is especially relevant for the Republic of Uzbekistan. The Concept for the development of the higher education system until 2030 envisages the wide introduction of digital technologies and distance learning into the educational process [1]; the Strategy “Digital Uzbekistan – 2030” sets priorities for the digital transformation of sectors of the economy and the social sphere, including education [2]; and the Strategy for the development of artificial intelligence technologies until 2030 sets the goal of raising the population's knowledge and skills in applying AI technologies and developing human resource capacity [3]. Universities are thus expected not only to adopt AI tools but also to ensure that these tools strengthen, rather than erode, students' capacity for independent learning.

The aim of this study is to synthesise current evidence on how GenAI influences students' SRL strategies in digital higher education and to identify the pedagogical conditions under which GenAI fosters rather than substitutes self-regulation. To achieve this aim, the following objectives were set: (1) to systematise the theoretical foundations of SRL relevant to GenAI-mediated learning; (2) to map the reported affordances and effects of GenAI onto the phases of SRL; (3) to identify risks to self-regulation and the factors that moderate them; (4) to propose a conceptual model and practical recommendations for universities.

The object of the research is the learning activity of university students in

GenAI-enhanced digital environments; the subject is the mechanisms and pedagogical conditions through which GenAI affects their SRL strategies. The study addresses three research questions: RQ1 – which SRL phases and strategies does GenAI support? RQ2 – what risks to self-regulation have been reported? RQ3 – under what conditions does GenAI foster rather than replace SRL? It is hypothesised that the effect of GenAI on SRL is not inherent in the technology itself but depends on instructional design that preserves the learner's metacognitive agency. The scientific novelty of the study lies in a phase-specific synthesis of the most recent (2023–2026) evidence, in the integration of supportive and risk-related findings into a single conditional model, and in its contextualisation for the digital higher education system of Uzbekistan.

LITERATURE REVIEW

Contemporary research on SRL draws on several theoretical models. Comparing six of the most influential of them, Panadero [25] shows that, despite differences in emphasis, they share a cyclical view of regulation organised around preparatory, performance and appraisal phases and integrate cognitive, metacognitive, motivational and emotional components. Zimmerman's social-cognitive model [38] remains one of the most widely applied. It describes SRL as a cycle of three phases: the forethought phase, which includes task analysis (goal setting and strategic planning) and self-motivation beliefs such as self-efficacy and intrinsic interest; the performance phase, which includes self-control through task strategies and self-observation through metacognitive monitoring; and the self-reflection phase, which includes self-judgement – self-evaluation and causal attribution – and self-reaction, which in turn feeds into subsequent forethought. Winne and Hadwin's model, by contrast, treats regulation as information processing that unfolds over task definition, goal setting and planning, enactment of tactics and strategies, and adaptation, each described in terms of conditions, operations, products, evaluations and standards (COPES) [25]. Because Zimmerman's model is explicit about the processes that take place before, during and after a task, it offers a convenient lens for analysing where an external tool such as GenAI intervenes in the learning cycle, and it was therefore adopted as the analytical framework of the present study.

The importance of SRL increases in digital higher education. Online learners have greater autonomy and fewer external cues from teachers and peers, so deficits in regulation translate more directly into poor achievement. In a systematic review of online higher education, Broadbent and Poon [7] found that time management, metacognition, effort regulation and critical thinking were associated with academic outcomes, whereas rehearsal, elaboration and organisation had the least empirical support. Wong et al. [31], reviewing interventions in online learning environments and MOOCs, concluded that SRL can be supported by instructional means such as prompts and feedback built into the learning environment. These studies established an important premise for the GenAI era: self-regulation in digital settings is not only a learner characteristic but also an outcome of design, which technology can either support or undermine.

Before the emergence of GenAI, research on artificial intelligence in higher

education concentrated on profiling and prediction, intelligent tutoring and adaptive systems. A meta-review of 66 evidence syntheses by Bond et al. [5] found that adaptive systems and personalisation were the most prominent applications, while ethical, methodological and contextual issues remained under-researched. Molenaar [22] proposed to view such technologies through the lens of hybrid human–AI intelligence, introducing a detect–diagnose–act framework of AI functions and a six-level model describing how control shifts between teachers and technology, and used SRL as an illustrative case. Interview data collected by Jin et al. [16] show that university students regard AI applications as useful for metacognitive, cognitive and behavioural regulation, but not for the regulation of motivation, and that they expect such tools to take into account learner identity, activeness and position. Järvelä, Nguyen and Hadwin [15] extended the discussion to collaborative learning by proposing a hybrid model of human–AI shared regulation built around the concept of “triggers” – situations that call for regulation.

With the arrival of GenAI, attention shifted from systems that adapt to the learner to systems with which the learner converses. Chang et al. [9] formulated three design principles for AI chatbots grounded in Zimmerman's model: teaching students to write prompts for goal setting, configuring chatbots to ask students reverse questions that prompt self-monitoring, and using learning analytics to help students reflect on and adjust their strategies. Chiu [10], on the basis of a Delphi study with 36 teachers, developed a classification of 20 ChatGPT-based learning activities that shows how each activity satisfies basic psychological needs and supports each SRL phase. Lodge, de Barba and Broadbent [20] argued that AI literacy and critical thinking alone are insufficient and proposed a “network of co-regulation” that places the learner and his or her agency at the centre of human–AI learning. Early empirical evidence also came from school settings: in a three-week science unit, a GenAI-based chatbot enhanced secondary students' knowledge, behavioural engagement and motivation, and the number of interactions predicted variation in their SRL [23].

In parallel, a body of research has documented the risks of delegating cognitive work to AI. Cognitive offloading – the use of physical action or external tools to reduce the cognitive demands of a task – can be beneficial, but it also changes which processes the learner actually performs [26]. A systematic review by Zhai, Wibowo and Li [36] links over-reliance on AI dialogue systems to weaker decision-making, critical thinking and analytical reasoning. In a randomised experiment with 1,625 students across ten courses, Darvishi et al. [11] found that students tended to rely on rather than learn from AI assistance: the quality of their peer feedback did not hold up once AI prompts were removed, and self-monitoring checklists only partly compensated for this effect. In a field experiment with nearly 1,000 high school students, Bastani et al. [4] showed that unrestricted access to GPT-4 improved practice performance by 48% but reduced subsequent unassisted performance by 17%, whereas a version with pedagogical guardrails largely mitigated this harm. Kasneci et al. [17] therefore stress that the effective use of large language models in education requires competencies that allow learners and teachers to understand the technology and its limitations.

The pedagogical and policy debate on GenAI reflects these opposing tendencies.

Kasneci et al. [17] describe large language models as tools that can personalise learning, support writing and research and assist teachers, while warning of over-reliance, bias, privacy problems and a possible weakening of critical thinking. The UNESCO guidance [21] formulates policy responses that include protecting human agency, monitoring and validating GenAI systems before their use in education, and developing the AI competencies of learners and teachers. In terms of SRL theory, protecting human agency means that decisions about goals, strategies and the evaluation of learning remain with the learner – the same issue that Molenaar [22] describes as the distribution of control between people and technology. The question for higher education is therefore not whether students will use GenAI, but which of these decisions they will continue to make themselves.

The literature thus reveals two parallel streams: one emphasising the potential of GenAI to scaffold SRL, and another documenting over-reliance and offloading. Existing syntheses have mostly examined AI in general, learning outcomes in general or design affordances, and only partly confront supportive and risk-related evidence within the same phase-based framework. Moreover, the most recent experimental studies of 2025–2026 have not yet been integrated, and evidence from Central Asian universities remains scarce. The present study addresses this gap by synthesising both streams of evidence along the phases of Zimmerman's model and by deriving the conditions under which GenAI fosters self-regulation.

METHODOLOGY

The study was designed as an integrative literature review [28]. This type of review was selected for two reasons. First, research on GenAI and SRL is an emerging field in which empirical studies, systematic reviews and conceptual frameworks coexist, and an integrative review allows these different types of sources to be analysed together. Second, the aim of the study was not only to summarise findings but also to derive a conceptual model, which is a typical purpose of integrative reviews. A statistical meta-analysis was not feasible: the available studies differed considerably in design, tasks, GenAI tools and outcome measures, which precluded the pooling of effect sizes. The review was carried out in five stages: formulation of the research questions, literature search, screening against eligibility criteria, data extraction and coding, and synthesis.

The literature search was conducted in October 2026. Academic search engines and the publisher platforms ScienceDirect, Wiley Online Library, SpringerLink, Nature Portfolio, SAGE Journals and MDPI were searched with combinations of three groups of terms: (“generative artificial intelligence” OR “generative AI” OR ChatGPT OR “large language model*”) AND (“self-regulated learning” OR self-regulation OR metacogniti*) AND (“higher education” OR universit* OR undergraduate*). The search was complemented by backward and forward snowballing of the reference lists of recent reviews. The bibliographic data of every retained publication were verified against Crossref records and publisher pages.

Publications were included if they (a) were peer-reviewed journal articles published between 2023 and 2026; (b) examined GenAI tools based on large language

models or, in the case of reviews, included GenAI among the applications analysed; (c) involved university students or, in the case of reviews and design frameworks, were applicable to higher education; (d) reported outcomes, processes or design principles related to at least one SRL phase, to metacognition or to learner regulation; and (e) were written in English. Studies with exclusively school-age participants, studies of non-generative AI, preprints, editorials and retracted publications were excluded; one retracted meta-analysis identified during screening was removed on this basis. Studies with school-age participants and studies of non-generative AI were, however, used as contextual evidence in the literature review and the discussion.

Application of these criteria resulted in a final corpus of 18 publications: nine empirical studies with university students [8, 13, 14, 19, 29, 30, 33, 35, 37], six systematic reviews and meta-analyses [12, 18, 24, 27, 32, 36], and three conceptual and design frameworks [9, 10, 20].

Data were extracted using a standardised form that recorded the authors and year, publication type, design, sample, GenAI tool or intervention, the SRL phases addressed, the direction of the reported effect (supportive, mixed or hindering) and the conditions under which the effect was observed. A finding was coded as supportive when the study reported a statistically significant improvement or a predominantly positive pattern in an SRL-related outcome, as hindering when it reported a decline or a negative association, and as mixed when it reported improvements in some outcomes alongside null or negative effects in others. The analysis combined deductive and inductive coding. Deductively, each finding was assigned to the forethought, performance or self-reflection phase of Zimmerman's model [38]. Inductively, risks and moderating conditions were identified through thematic analysis following the six phases described by Braun and Clarke [6]: familiarisation with the data, generation of initial codes, searching for themes, reviewing themes, defining and naming themes, and producing the report. To ensure transparency and replicability, the characteristics of all included empirical studies are reported in Table 1, and every synthesised statement in the following section is linked to its source.

Because the reviews in the corpus partly overlap with the primary studies, their findings were used to characterise general tendencies, whereas the phase-level synthesis relied primarily on the primary studies. Differences in design were taken into account during synthesis: findings from randomised and quasi-experimental studies were treated as stronger evidence than those from cross-sectional surveys, which can establish associations but not causal effects.

ANALYSIS AND RESULTS

The 18 publications in the corpus were published between 2023 and 2026: three in 2023, six in 2024, five in 2025 and four in 2026. The nine empirical studies involved a total of 1,394 university students, with sample sizes ranging from 46 to 399. Seven of them used experimental or quasi-experimental designs with comparison groups, and two were cross-sectional surveys. The GenAI applications studied included general-purpose ChatGPT use, ChatGPT-supported writing, scientific inquiry and creative problem-solving, GenAI-based learning with metacognitive support, and GenAI

feedback combined with learning analytics. The characteristics of the empirical studies are summarised in Table 1.

Table 1.

Characteristics of the included empirical studies (n = 9)

Study	Design and sample	GenAI use	Main SRL-related findings
Chan & Hu, 2023 [8]	Survey; 399 undergraduate and postgraduate students, Hong Kong	General use of GenAI	Perceived benefits: personalised learning support, writing, brainstorming, research; concerns about accuracy, privacy, ethics and personal development
Essel et al., 2024 [13]	Pretest–posttest control-group design, mixed methods; 125 undergraduates (60/65), Ghana	ChatGPT for in-class tasks in a flipped research methodology course	Gains in critical, reflective and creative thinking compared with the database and search engine group
Stadler et al., 2024 [29]	Randomised experiment; 91 university students	ChatGPT-3.5 vs Google search in a scientific inquiry task	Lower cognitive load; lower quality of reasoning and argumentation
Urban et al., 2024 [30]	Preregistered experiment; 77 students with and 68 without ChatGPT	ChatGPT in creative problem-solving	Higher solution quality ($d = 0.69$) and task self-efficacy ($d = 0.65$); less mental effort ($d = 0.58$); self-evaluations unrelated to performance
Zhou et al., 2024 [37]	Survey, PLS-SEM; 223 undergraduate and postgraduate students, China	General use of GenAI	Ease of use → self-regulation → critical thinking and problem-solving; no indirect effect of usefulness and learning value
Fan et al., 2025 [14]	Randomised experiment, four conditions; 117 university students	ChatGPT vs human expert vs writing analytics vs no support in essay writing	Largest essay score gain with ChatGPT; no differences in knowledge gain and transfer; different SRL process patterns; risk of “metacognitive laziness”
Xu et al., 2025 [33]	Quasi-experiment, 4 weeks; 68 college students (35/33)	GenAI-based learning with vs without explicit metacognitive support	Support improved SRL (task strategies, self-evaluation) and learning experience; no difference in achievement; SRL risked declining without support
Yilmaz et al., 2026 [35]	Mixed methods, comparison design; 46 students in online higher education	GenAI feedback informed by trace data vs tutor feedback	Improvement in the task strategies dimension of SRL; GenAI feedback rated higher in genuineness; perceptions of the feedback source mattered
Lawanna, 2026 [19]	Quasi-experiment, 12 weeks; 180 undergraduates	GenAI-powered reflective learning dashboard vs instructor feedback	Improved SRL behaviours, time on task, login frequency and performance ($p < .001$); higher motivation and agency (qualitative data)

The six reviews and meta-analyses each covered between 14 and 73 primary

studies. The meta-analysis of 69 experimental studies published in 2022–2024 reported that ChatGPT use improved academic performance, affective-motivational states and higher-order thinking and reduced mental effort, but did not change students' self-efficacy [12]. A systematic review of 38 studies found that 71.4% of them reported a positive role of GenAI in SRL, mainly through personalised learning, metacognitive support and adaptive feedback, and 62.5% reported a positive role in critical thinking; the same review recorded warnings about over-reliance [27]. The evidence is summarised by SRL phase in Table 2 and described below.

Table 2.
 GenAI affordances, reported effects and risks across the phases of SRL

SRL phase	GenAI affordances and activities	Reported supportive effects	Reported risks and null effects
Forethought	Personalised learning objectives; finding and integrating resources; prompting for goal setting; information search [9, 32]	Higher task self-efficacy [30]; perceived personalised learning support [8]	No change in self-efficacy in pooled experimental evidence [12]; task definition and goal setting under-addressed by interventions [24]
Performance	Recommending strategies; monitoring progress; generating ideas and examples; dialogic, context-adaptive scaffolding [24, 32]	Better task products [12, 14, 30]; improved task strategies [33, 35]; more SRL behaviours and time on task [19]; gains in higher-order thinking [13]	Reduced mental effort and lower depth of reasoning [29, 30]; output gains without knowledge gain or transfer [14]; over-reliance and heuristic shortcuts [36]
Self-reflection	Feedback; self-assessment; recording progress with feedback; reverse questioning; reflective dashboards [9, 19, 32]	Improved self-evaluation with metacognitive support [33]; positive perception of GenAI feedback [35]; higher motivation and agency [19]	Miscalibrated self-evaluations [30]; dependence on the perceived source of feedback [35]; decline of SRL without support [33]

The review of 73 articles by Xia et al. [32] identified creating personalised learning objectives and finding and integrating resources as GenAI affordances for this phase, with information searching as the most common student activity. Design frameworks proposed teaching students to prompt GenAI for goal setting [9] and classified ChatGPT-based activities for each SRL phase [10]. In the experiment by Urban et al. [30], ChatGPT increased students' task-related self-efficacy ($d = 0.65$) and led them to perceive the task as easier ($d = 0.56$). In contrast, the meta-analysis by Deng et al. [12] found no change in self-efficacy. A comparative review of 70 articles [24] reported that AI-based SRL interventions focused mainly on task execution and evaluation and paid less attention to task definition, goal setting and adaptation.

This phase was represented by the largest number of findings. GenAI use was associated with better task products: higher essay scores [14]; higher quality ($d = 0.69$), elaboration ($d = 0.61$) and originality ($d = 0.55$) of creative solutions [30]; and gains in critical, reflective and creative thinking [13]. At the same time, students using GenAI

reported lower cognitive load [29] and less mental effort ($d = 0.58$) [30], and in scientific inquiry their recommendations showed lower-quality reasoning and argumentation than those of students using a conventional search engine [29]. In the four-condition experiment by Fan et al. [14], the ChatGPT group achieved the largest improvement in essay scores, but knowledge gain and transfer did not differ among the groups, whereas the frequency and sequences of SRL processes did.

With respect to learning strategies, explicit metacognitive support during GenAI-based learning improved task strategies [33], GenAI feedback informed by trace data improved the task strategies dimension of SRL [35], and a GenAI-powered reflective dashboard increased SRL behaviours, time on task and login frequency [19]. In the survey by Zhou et al. [37], the perceived ease of use of GenAI enhanced students' self-regulation, which in turn supported critical thinking and problem-solving, whereas perceived usefulness and learning value had no indirect effect through self-regulation. According to Nguyen et al. [24], GenAI mainly provided dialogic, context-adaptive cognitive scaffolding and content generation, whereas earlier AI systems mainly provided analytics-driven scaffolding.

Obtaining feedback and self-assessment were the most common GenAI-supported student activities in this phase [32]. Explicit metacognitive support improved self-evaluation, whereas students without such support risked a decline in SRL [33]. Students rated GenAI feedback more positively than tutor feedback, notably in genuineness, but some indicated that their attitudes might have differed had they known the source of the feedback [35]. Qualitative data from the dashboard study pointed to increased motivation and learner agency [19]. Urban et al. [30], in contrast, found that students' self-evaluations did not correlate with their actual performance and that the perceived usefulness of ChatGPT was associated with greater inaccuracy of self-evaluation.

Three types of risk recurred across the corpus: reduced cognitive engagement [12, 29, 30]; over-reliance and a preference for fast solutions and heuristics [27, 36]; and the “metacognitive laziness” described by Fan et al. [14]. The qualitative review of 14 studies by Lan and Zhou [18] found that AI can support all three SRL phases but that the locus of agency – human or AI – shapes how the SRL process unfolds. Among the experimental studies, improvements in SRL processes themselves (task strategies, self-evaluation, SRL behaviours) were reported in the three studies in which GenAI use was combined with explicit metacognitive support or with reflective feedback based on learning analytics [19, 33, 35]. In the studies of unstructured GenAI use, gains in task performance were accompanied by lower depth of reasoning or by the absence of differences in knowledge gain and transfer [14, 29].

DISCUSSION

The results make it possible to answer the research questions. With regard to RQ1, GenAI supports all three phases of SRL, which is consistent with earlier reviews [18, 32]. The evidence is, however, asymmetric: the performance phase is by far the best documented, whereas the forethought phase – goal setting, planning and the formation of motivational beliefs – remains under-addressed by interventions [24].

This asymmetry matters because, according to Zimmerman [38], the quality of forethought determines which strategies a learner selects and the standards against which performance is later evaluated.

A central finding of the review is the gap between performance and learning. GenAI reliably improves the products students create [12, 14, 30], but these improvements do not necessarily translate into deeper reasoning, knowledge gain or transfer [14, 29]. In terms of SRL theory, GenAI thus functions primarily as a performance amplifier rather than a regulation amplifier. This interpretation agrees with the evidence from online higher education that achievement depends on metacognition and effort regulation rather than on surface strategies [7]: when the tool absorbs the effortful part of regulation, the mechanism underlying long-term achievement may be bypassed.

On this basis, a conditional model of the role of GenAI in SRL is proposed (Figure 1). It maps the GenAI affordances identified in the review onto Zimmerman's three phases and introduces the regulatory locus as its key element. When the learner retains metacognitive agency, GenAI acts as a regulation amplifier; when control shifts to the tool, it acts as a regulation substitute.

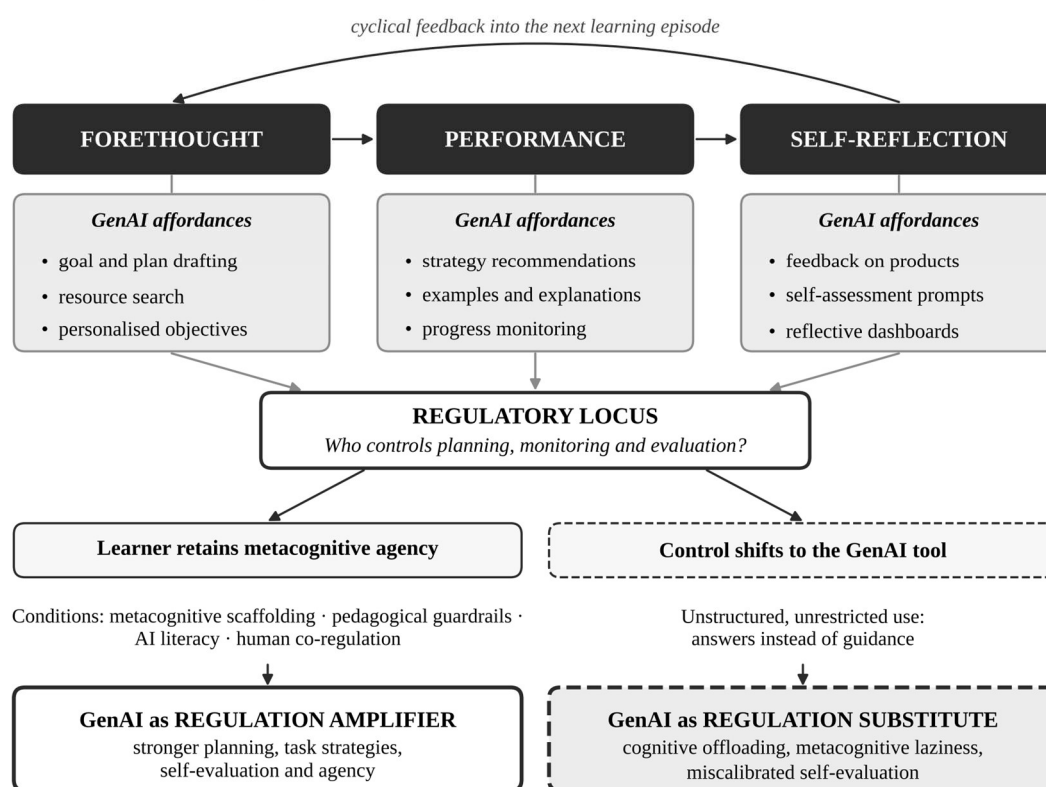


Figure 1. Conditional model of the role of GenAI in self-regulated learning

With regard to RQ2, the risks identified can be explained by the theory of cognitive offloading [26]. Offloading is adaptive when it frees cognitive resources for higher-order processing, but harmful when it removes precisely the processing that produces learning. The reduced mental effort reported in several studies [12, 29, 30] is therefore ambivalent: it may reflect efficiency, but it may equally reflect the “metacognitive laziness” described by Fan et al. [14]. Similar reliance effects were

observed for non-generative AI assistance [11] and among high school students [4]. The miscalibration of self-evaluations [30] deserves particular attention, since accurate monitoring is the basis for every control decision in the SRL cycle [25, 38]. The apparent contradiction between increased task self-efficacy [30] and the absence of an effect on self-efficacy in pooled experimental evidence [12] may be explained by the difference between momentary, task-specific confidence in the presence of the tool and more stable beliefs about one's own learning ability. Confidence that is not matched by accurate self-evaluation should not be equated with stronger self-regulation.

With regard to RQ3, the evidence indicates that the decisive variable is not the presence of GenAI but the locus of regulatory control. SRL processes improved when GenAI was combined with explicit metacognitive support [33] or with reflective feedback grounded in learning analytics [19, 35], and harm was mitigated when the AI tutor was configured with pedagogical guardrails [4]. These findings support the hypothesis of the study and are consistent with hybrid human–AI perspectives on learning regulation, which focus on how control is distributed between the learner and technology [15, 20, 22].

The model has several practical implications for universities, including those of Uzbekistan, where digital learning is expanding within the framework of national strategies [1, 2]. First, assignments can be structured as a “plan – prompt – reflect” cycle: students formulate goals and a plan before consulting GenAI and afterwards submit a short reflection on how they used it, which brings the under-supported forethought phase back into the learning process. Second, institutional GenAI assistants can be configured as tutors that ask guiding and reverse questions instead of delivering complete answers [4, 9]. Third, AI literacy and SRL training should be integrated into curricula, in line with the national priority of developing the population's AI skills [3] and with the human-centred approach advocated by UNESCO [21]. Fourth, teachers need professional development in designing GenAI-supported SRL activities, for which classification tools such as that of Chiu [10] provide a starting point. Finally, data from learning management systems can be combined with GenAI-generated feedback to support student reflection [19, 35].

The study has several limitations. As an integrative review, it does not claim exhaustive coverage of all publications, and only English-language peer-reviewed sources were included. The number of empirical studies with university students is still small, their designs and measures are heterogeneous, and the interventions lasted from a single session to twelve weeks, which does not allow conclusions about long-term effects or the fading of novelty effects. Some findings rely on self-reported measures, and GenAI itself evolves faster than the research cycle. Finally, no study conducted in Central Asia was identified, and the transferability of the conclusions to Uzbek universities requires empirical verification.

CONCLUSION

This study set out to clarify the role of generative artificial intelligence in fostering self-regulated learning strategies in digital higher education. The synthesis of 18 recent publications shows that GenAI can support all three phases of SRL –

forethought, performance and self-reflection – but that the evidence is concentrated in the performance phase and that gains in task performance do not automatically translate into learning or into better self-regulation.

The answer to the central research question is therefore conditional. GenAI fosters SRL when the learner retains metacognitive agency, that is, when its use is accompanied by metacognitive scaffolding, pedagogical guardrails, reflective feedback and AI literacy. Without these conditions it tends to substitute for regulation, giving rise to cognitive offloading, metacognitive laziness and inaccurate self-evaluation. The hypothesis that the effect of GenAI on SRL depends on instructional design rather than on the technology itself is thus supported.

The contribution of the study lies in a phase-specific synthesis of supportive and risk-related evidence and in a conditional model that distinguishes GenAI as a regulation amplifier from GenAI as a regulation substitute. Its practical significance lies in recommendations on assignment design, the configuration of institutional AI assistants, AI literacy and teacher development, which can inform university policies on the responsible use of GenAI, including in Uzbekistan. For Uzbek universities, the results suggest that the implementation of national strategies on digitalisation and artificial intelligence in higher education should be accompanied by explicit attention to students' self-regulation, not only by wider access to AI tools, and the proposed model can serve as a framework for designing and evaluating such measures.

Future research should include longitudinal studies based on process and trace data, experiments in Uzbek and other Central Asian universities, studies of GenAI support for the forethought phase and for motivation regulation, and research on how students use GenAI in different languages of instruction.

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