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SYSTEMATIC ANALYSIS OF GENERATIVE ARTIFICIAL INTELLIGENCE IN ENHANCING SELF-REGULATED LEARNING IN LIFE AND EARTH SCIENCES

M. Belmajdoub [1] A. Essedaoui [1,2] S. Belaaouja [1]

1. Laboratory of Education, Sciences, and Technology, Higher School of Education and Training of Berrechid, Hassan I University, Settat, Morocco, moncef.belmajdoub.doc@uhp.ac.ma, sabah.belaaouja@uhp.ac.ma
2. Employability of Sciences and Engineering in Education and Training, Regional Center for Education and Training Professions, Casablanca-Settat, El Jadida, Morocco, essedaouiaafaf20@gmail.com

Abstract- Digital transformation is reshaping education and reinforcing the importance of self-regulated learning (SRL). In Life and Earth Sciences (LES), generative artificial intelligence (GAI) can support scientific reasoning, but its impact on SRL at the secondary level remains unclear. In this context, this study draws on existing work to examine the impact of generative artificial intelligence on autonomous learning in Life and Earth Sciences at the secondary level. It aims to understand how generative artificial intelligence influences learners' autonomy in Life and Earth Sciences at the secondary level and under what conditions it can improve learning without replacing the effort of reflection. To this end, we conducted a systematic review based on scientific articles. The search covered the period 2019-2025 and focused on indexed journals: Scopus, Taylor & Francis, Springer et Web of Science. Initially, 1605 articles were identified. After screening and selection, 12 studies were retained. We applied an analytical synthesis model that codes Al use types (planning support, tutoring, feedback/assessment, content generation, personalization, simulations, and governance) and SRL components (forethought/planning, performance/monitoring, self-reflection/evaluation, and motivation/engagement). Across the corpus, self-reflection/self-assessment was addressed in 9/12 studies (75%), monitoring in 8/12 (67%), planning/time management in 7/12 (58%), and motivation/engagement in 7/12 (58%). Although 4/12 studies were predominantly benefit-oriented, 8/12 highlighted substantial risks (over-reliance, hallucinations, superficial understanding, and academic integrity), indicating that outcomes depend strongly on task design and teacher scaffolding. Future research should test these uses in the classroom over the long term and analyze teachers' understanding, motivation, and training needs.

Keywords: Generative artificial intelligence, self-regulated learning, Life and Earth Sciences, Secondary education, Systematic review, PRISMA

1. INTRODUCTION

In today's world, digital transformation is changing many areas, including education. Autonomy is an essential skill for learning today and in the future. Several studies [5, 16] show that artificial intelligence (AI) can support learning, especially in science subjects. In Life and Earth Sciences, learners must observe, understand, and explain phenomena. Because this subject requires reasoning, generative AI can be a valuable aid in guiding learners, provided that it is used with caution. In secondary school, independent learning remains difficult for many learners. Some struggle to plan an activity, manage their time, or check whether they have truly understood. Others seek a quick answer and overlook the explanation, which can reduce their understanding of the concepts [9].

In a global context marked by digital transformation, the integration of artificial intelligence (AI) into education opens up new opportunities to support learner autonomy, particularly in scientific disciplines [5, 9]. Since November 2022, when ChatGPT was made available to the public, generative artificial intelligence (GAI) has become a part of education, especially in secondary schools [18, 19]. This arrival has led to different opinions. Some people want these tools to be used in schools, while others want to ban or limit their use because of the possible dangers to education. Still others say we should be careful. At the same time, the use of GAI by teachers to offer a more personalized educational experience is often presented as a positive development [9].

The introduction of Al into educational practices therefore raises several issues. On the one hand, Al can offer tools that give people more independence. On the other hand, people are starting to worry about too much reliance on digital technologies and the risk of making learners less able to think critically. Some studies [5, 15] say that Al can be good for education, but it needs to be used carefully and watched closely. In Life and Earth Sciences (LES), a subject with a strong experimental and reflective component, Al can also offer tools for finding information, simulating processes, and creating personalized learning experiences.

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In this context, this review looks at how generative AI affects learning in Life and Earth Sciences in secondary schools. It looks at how well these tools can support students' independence and participation in LES at the secondary level. It also looks at the conditions under which they can improve learning without replacing the effort of reflection.

2. METHODOLOGY

2.1. Search Strategy and Study Selection

The methodological approach has three main steps. The first step is to create a research question. What effect does the use of GAI have on secondary school students' independent learning in Life and Earth Sciences? To create this question, we used the PICO method [12], which focuses on the context of studies (Table 1): The population is the group of people who are involved. The intervention is what is used. The comparison is what is compared. The outcome is what is measured. This framework helps to better organize the research question and make it clearer and more precise.

Table 1. Summary of PICO elements relating to the use of generative AI tools in secondary school

P (Population)	Secondary students studying life and earth sciences
I (Intervention)	AI tools (ChatGPT, Copilot, Gemini....)
C (Comparison)	Traditional learning (without AI)
O (Outcome - Result)	Impact on students' independent learning

The second step involves conducting a literature search relevant to the research question. To do this, we followed the recommendations of the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) statement [13] and searched indexed bibliographic databases, namely Scopus, Taylor & Francis, Springer, and Web of Science. Using PICO decomposition, we developed a keyword combination as follows: (“Generative Artificial Intelligence” OR “GAI tools”) AND (“self-regulated learning” OR “autonomous learning” OR “learner autonomy”) AND (“secondary education” OR “high school”) AND (“biology” OR “geology” OR “life and earth sciences”).

Given the rapid evolution of AI, the inclusion criteria (Table 2) focused on publications from 2019 to 2025 (search conducted in June 2025) and written in English. We included peer-reviewed journal articles and full peer-reviewed conference papers that addressed generative AI tools (for example ChatGPT) in secondary education science settings (with an emphasis on Life and Earth Sciences) and reported outcomes or implications relevant to student SRL (planning, monitoring, self-assessment, motivation) and/or the pedagogical conditions required to foster autonomy. Regarding the exclusion criteria, publications that were irrelevant or did not meet the thematic and chronological criteria were excluded. Table 2 presents the inclusion and exclusion criteria applied in this systematic review.

Table 2. Inclusion and exclusion criteria for the systematic review

Inclusion criteria	
Search criteria	Values
Year of publication	2019-2025
GAI in science education	- Title contains: “generative artificial intelligence” AND “sciences” AND “education”
GAI in relation to independent learning and assessment in life and earth sciences	- Abstract contains: (“self-regulated learning” OR “autonomous learning” OR “Learner autonomy”) AND (“biology” OR “geology” OR “life and earth sciences”)
Type of article	- Peer-reviewed journal articles and full peer-reviewed conference papers
Type of sources	- Journals, conference proceedings, and book series
Exclusion criteria	
Search criteria	Values
Article language	Not in English
Article type	Editorials, Letter, Book, and data document
Subject	- Deals with AI in general without focusing on generative AI as defined in this research

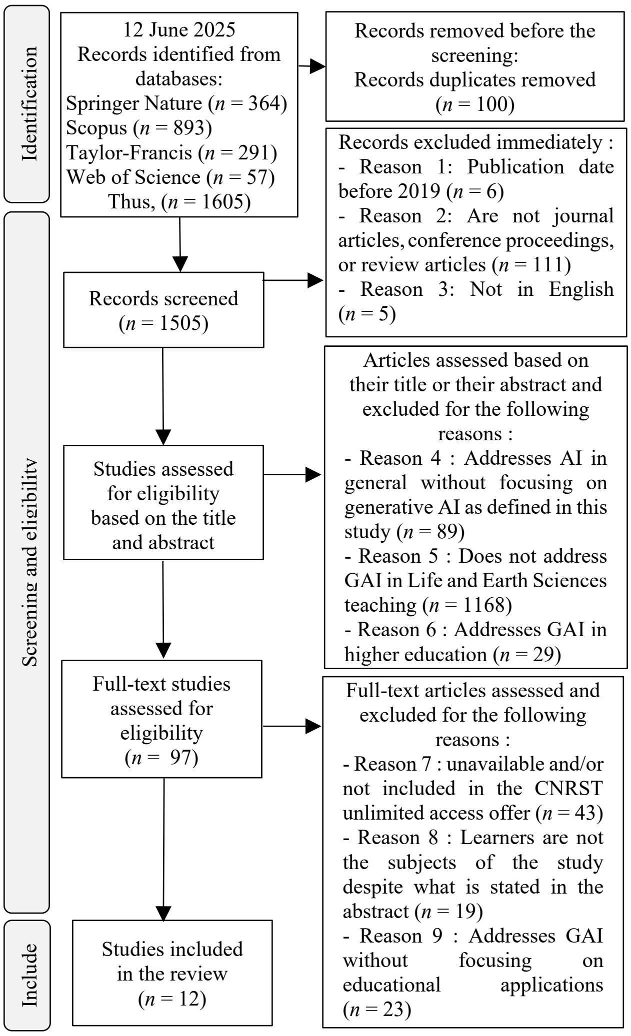

Figure 1. PRISMA flowchart for study selection

The third step consists of applying filters. A total of 1605 articles were initially identified for screening, as shown in study selection strategy illustrated in Figure 1.

First, the initial identification phase resulted in 1505 articles after duplicates were removed. An initial screening conducted using the Python-based tool ASReview LAB excluded 1286 articles, as their titles and abstracts indicated that the main topic did not match the scope of the present study. Next, the abstracts of the remaining 97 studies were re-examined, and a further 85 articles were excluded from the corpus due to unavailability and/or because they addressed GAI without focusing on educational applications. Finally, 12 studies were included, representing approximately 0.75% of the total.

2.2. Analytical Synthesis and Coding Framework

The included studies were synthesized using a structured coding approach. Each study was coded along two analytic axes. The first axis captured the primary function of AI use in learning activities (planning support, tutoring/explanations, feedback and self-assessment, content generation, assessment support, personalization/recommendation, and policy/training). The second axis captured self-regulated learning (SRL) components. These components were grouped as follows: planning (goal setting and strategy selection), monitoring (tracking progress and adjusting actions), evaluation/reflection (judging quality and revising), and motivation/engagement (persistence, effort regulation, and self- efficacy). The decisions about coding were based on clear signs reported in the methods and results of each study (such as measures, stated outcomes, or clearly described effects). If the results of a study addressed more than one dimension, that study could be assigned to multiple SRL components. The final coded dataset (Table 3) was then put together to make the cross-study tables and frequency-based percentages reported in the Results section.

Table 3. Coding scheme used for analytical synthesis

Layer	Category	Operational definition	Examples of indicators
SRL	Planning (forethought)	Goal setting, planning steps, strategy selection before the task	goal statements, planning prompts, study plans
	Monitoring (performance)	Self-checking, tracking progress, regulation during task	self-questioning, verification, error checking
	Evaluation (reflection)	Self-evaluation, reflection after task, attribution	post-task reflection, rubric-based self-rating
	Motivation	engagement, self-efficacy, persistence, interest	motivation scales, engagement logs
GAI use	Planning support	AI used to plan tasks / structure work	outlines, step plans
	Tutoring / explanations	AI used to explain concepts and scaffold understanding	Q&A tutoring, worked examples, clarifications
	Feedback / self-assessment	AI used to critique, assess, suggest improvements	feedback loops, rubric feedback, revision suggestions
	Content generation	AI used to generate drafts/materials (text/code/questions)	drafting, summarizing, practice items generation
	Assessment redesign	AI used to redesign assessment / integrity strategies	authentic assessment, oral defense, process grading
	Personalization / recommendation	AI used to tailor guidance / resources	adaptive recommendations, personalized paths
	Simulation support	AI used for simulations / scenarios / inquiry support	simulated tasks, "what-if" exploration
	Policy / training	AI used / discussed for policies, ethics, AI literacy	guidelines, AI literacy, governance

2.3. Calculation of Synthesis Indicators

Percentages reported in this review were derived from the study-level coding. For each category, we counted the number of studies in which the code was present (k) and divided by the total number of included studies (n = 12), then multiplied by 100: Percentage = (k/N) × 100. For example, if monitoring is coded in 9 studies, the percentage is (9/12) × 100 = 75.0%. Because a single study can receive multiple codes, percentages across SRL components do not sum to 100%

3. RESULTS

3.1. Characteristics of the Studies Selected

The 12 included studies show a mix of results about GAI use in educational settings. They include different types of studies, such as comparative studies, studies based on surveys or interviews, and studies that look at ideas or analyze existing data. As shown in the comparison table (Table 4), the included literature covers many different subjects, including science education and life and earth sciences. It also looks at different ways to use GAI, such as ChatGPT based tools, generative chatbots, and other GAI applications. The variety of situations and ways to measure things makes it difficult to combine effect sizes directly. But it helps to combine results from different studies by putting them into categories.

3.2. Cross-Study Analytical Synthesis of GAI Impacts on SRL and Learning-Related Outcomes

We conducted a quantitative aggregation based on study-level coding and vote counting. Each study was classified according to its overall conclusion regarding GAI impact as positive, mixed, or cautionary (Figure 2).

Overall, the distribution is dominated by mixed conclusions, indicating that reported benefits are frequently conditional on how GAI is implemented and supervised.

We further quantified how often SRL components were addressed across the included studies using frequency synthesis (Table 5). Monitoring/performance and self-reflection/evaluation are the most frequently addressed SRL components, while motivation/engagement and forethought/planning are reported in fewer studies.

Table 4. Comparative analytical matrix of included studies (*n* = 12)

Study	Study type	Sample size	Subject area	GAI tool	SRL dimension(s)	Main effect and reported limitations
Lee et al. (2024)	Survey + interviews (educators' perspectives)	Survey *n* = 30; interviews *n* = 8	High education teaching & learning	Generative AI (Chat GPT)	Self-reflection / evaluation	Ambivalent perceptions; assessment modifications common; strong need for support / training; integrity concerns. Limitations: Single institution; small sample; perceptions not outcomes.
Al Darayseh (2023)	Teacher survey (TAM-based)	*n* = 83 science teachers	Science teaching (UAE government schools)	AI applications (science education)	Not directly assessed (enabling / contextual)	High acceptance linked to self-efficacy, perceived usefulness / ease of use; anxiety not significant predictor. Limitations: Cross-sectional; self-report; not SRL outcome.
Balaz et al. (2024)	Controlled experiment	*n* = 23 (ChatGPT = 14; control = 9)	Programming education (component programming)	ChatGPT	Monitoring/performance; Self-reflection/evaluation	= 3x faster completion but risk of superficial engagement / uniform solutions; may reduce deep understanding. Limitations: Small sample; group imbalance; one task; short exposure.
Tao et al. (2025)	Bibliometric analysis (topic modelling)	1158 papers	Generative AI in education (cross-domain)	Generative AI (Chat GPT)	Planning / forethought; Monitoring / performance; Motivation / engagement	Maps 12 research topics (automated feedback, emotional engagement, personalized recommendation, simulation environments). Limitations: Secondary bibliometric evidence; does not estimate causal SRL effects.
Ng et al. (2024)	Pilot comparative study (GAI and rule-based chatbot)	*n* = 74 Secondary 4 students (3-week intervention)	Secondary science learning (Hong Kong)	SRLbot (ChatGPT-based) and Nemobot	Planning / forethought; Monitoring / performance; Self-reflection / evaluation; Motivation / engagement	Improved SRL indicators, science knowledge, behavioural engagement and motivation and control. Limitations: Short duration; single context; novelty effect; some self-report measures.
de Putter-Smits et al. (2025)	Qualitative interview study	N/A interviews	Science teacher education programs	GAI (ChatGPT)	Self-reflection / evaluation; Monitoring / performance	Identifies potential uses and new learning goals; emphasizes need for clear policy / guidelines; notes plagiarism / superficial engagement risks. Limitations: Sample size not available in abstract we accessed; perceptions not classroom outcomes.
Agathokleous et al. (2023)	Perspective / discussion paper	N/A (examples from interactive sessions with ChatGPT)	Biology & environmental science	ChatGPT	Planning / forethought; Monitoring / performance	Discusses benefits (speed / simplification of complex tasks) and risks / limitations across education / research / publishing. Limitations: Not empirical; illustrative examples.
Williams (2025)	Conceptual dialogue / critical evaluation	N/A	Bioscience high education	LLMs (ChatGPT)	Planning / forethought; Self-reflection / evaluation	Explores opportunities and constraints of LLMs for teaching / learning; emphasizes critical use. Limitations: No empirical outcomes; dialogue format.
Choi (2025)	Design-based mock lesson study	*n* = 3 pre-service teachers; one-session mock lesson	Earth science education (pre-service teachers)	GAI (for simulations / mock lessons)	Planning/forethought; Monitoring; Self-reflection/evaluation	Reports practical characteristics of GAI-supported mock lessons; highlights need for teacher expertise and critical integration. Limitations: Very small sample; short duration.
Li et al. (2025)	Conceptual / application analysis	N/A	Landscape ecology teaching	ChatGPT	Planning / forethought; Monitoring; Motivation / engagement	Describes applications (personalized plans, monitoring progress, Q&A) and risks (over-dependence, accuracy, ethics). Limitations: No empirical evaluation; relies on illustrative examples.
Diab & Almekhlafi (2025)	Qualitative case study (Straussian grounded theory)	Interviews *n* = 15 science teachers; 1074 coded segments	High school science lessons (UAE IAT)	ChatGPT	Monitoring / performance; Motivation / engagement	Identifies themes (AI literacy, curriculum alignment, equity, ethics) and proposes PRISM-AI framework incl. monitoring. Limitations: Preprint; teacher perspectives; no student outcome measures.
Chiu (2023)	Conceptual framework / review (Interactive Learning Environments)	N/A	Education practices / policies / research directions	ChatGPT & Midjourney (GAI)	Planning / forethought; Monitoring /; Self-reflection / evaluation; Motivation / engagement	Proposes conceptual roles of GAI across learning / teaching / assessment / administration; notes SRL tasks as part of learning design. Limitations: Not empirical; broad scope.

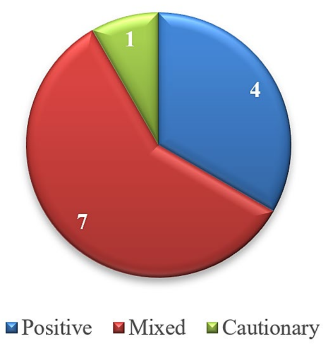

Figure 2. Distribution of AI impact categories across included studies

Table 5. Frequency of included studies addressing each SRL component (counts are not mutually exclusive)

SRL component	Studies (n)	Percent of studies
Forethought / planning	7	58.3%
Performance / monitoring	8	66.7%
Self-reflection / evaluation	9	75.0%
Motivation / engagement	7	58.3%

Figure 3 shows that planning support is the most common use of GAI across SRL components. It is followed by feedback / self-assessment and policy / training / governance. These patterns show that the impact of SRL is often based on how it is implemented and supervised.

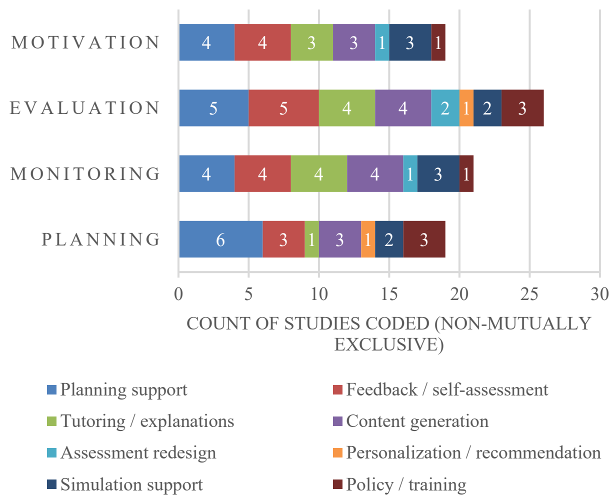

Figure 3. GAI use types with SRL components

Finally, to distinguish synthesized author insight from cited claims, we critically weighted the evidence base by design robustness and SRL measurement status (Table 6). Comparative empirical evidence remains limited relative to surveys, interviews, conceptual, and secondary analyses; therefore, the strongest claims are those supported by more robust comparative designs and clearer SRL coding, while broader conceptual work primarily informs mechanisms, risks, and implementation conditions rather than effect magnitude.

Table 6. Evidence weighting and magnitude reporting

Study	Evidence type	Magnitude reporting	Overall evidence weight
Lee et al. (2024)	Empirical (survey / qualitative)	Qualitative / Descriptive	Moderate (empirical; limited / indirect SRL)
Al Darayseh (2023)	Empirical (survey / qualitative)	Quantitative (statistics reported)	Moderate (empirical; limited / indirect SRL)
Balaz et al. (2024)	Empirical (comparative / experimental)	Quantitative (time ratio reported)	Moderate (empirical; limited indirect SRL)
Tao et al. (2025)	Secondary evidence (review / bibliometric)	N/A	Low (no primary outcomes)
Ng et al. (2024)	Empirical (comparative / experimental)	Qualitative/ Descriptive	High (comparative + SRL outcomes)
de Putter-Smits et al. (2025)	Empirical (survey / qualitative)	Qualitative/ Descriptive	Moderate (empirical; limited / indirect SRL)
Agathokleous et al. (2023)	Conceptual / perspective	N/A	Low (no primary outcomes)
Williams (2025)	Conceptual / perspective	N/A	Low (no primary outcomes)
Choi (2025)	Empirical (survey / qualitative)	Qualitative/ Descriptive	Moderate (empirical; limited / indirect SRL)
Li et al. (2025)	Conceptual / perspective	N/A	Low (no primary outcomes)
Diab & Almekhlafi (2025)	Empirical (survey / qualitative)	Qualitative / Descriptive	Moderate (empirical; limited / indirect SRL)
Chiu (2023)	Secondary evidence (review / bibliometric)	N/A	Low (no primary outcomes)

4. DISCUSSION

Across the included evidence base, GAI appears capable of supporting learner autonomy and SRL related processes, but the overall pattern is best characterized as conditional rather than uniformly positive (Figure 2). These patterns are consistent with the comparative and qualitative evidence summarized in Table 3. Apparent benefits are most defensible when GAI is positioned as a scaffold for example, to structure planning, prompt monitoring, and support reflective self-assessment-rather than as an unconstrained answer generator (Figure 3 and Table 5).

Importantly, the literature also reveals a persistent efficiency-understanding trade-off: faster task completion and immediate productivity may coexist with superficial processing and reduced conceptual depth. This tension helps explain why findings vary across studies and why "autonomy" can be interpreted differently depending on whether it reflects genuine self-regulation or the outsourcing of regulation to the tool.

Methodological heterogeneity further limits strong causal claims. Designs range from small-scale comparative studies to surveys/interviews and conceptual or secondary analyses (Table 4), and SRL is measured inconsistently (direct scales, proxies, or not measured).

Many studies are short-term and context-bound, which constrains inference about durable SRL development over time. These constraints justify a frequency-based synthesis rather than pooled-effect meta-analysis (Table 5 and Figure 3) and motivate the critical weighting of evidence (Table 6). The review also highlights risks that are ethical, pedagogical, and cognitive.

Ethical risks include academic integrity concerns and inequities in access; cognitive risks include over-reliance, reduced critical evaluation, and miscalibration driven by unreliable outputs. A problem-solving approach therefore requires explicit instructional safeguards: verification routines, process-oriented assessment, transparent usage policies, and teacher-guided prompt scaffolding (Table 7).

Table 7. Risk-benefit matrix for generative AI use in secondary LES

AI use type	Potential SRL benefits	Key risks	Mitigation / instructional conditions
Planning support (study plans, goal prompts, time management)	Forethought: goal setting, planning routines; reduced cognitive load for organization	Learners may outsource goal-setting; reduced ownership; plans may be unrealistic	Require learners to justify goals, compare AI plan with their constraints, and keep reflective logs; teacher checks periodically
Tutoring / explanations (Q&A, worked examples)	Performance: supports strategy use and monitoring; clarifies misconceptions	Hallucinated or oversimplified explanations; passive copying; shallow learning	Use verification prompts (sources, evidence), require explanation-in-own-words, and incorporate oral questioning or inquiry tasks
Feedback / self-assessment (quizzes, real-time feedback)	Self-reflection: immediate error detection and self-correction; supports metacognitive monitoring	Over-trust in feedback; miscalibration; reduced peer/teacher dialogue	Combine AI feedback with teacher feedback; require confidence ratings and error analysis; keep rubric-based checks
Content generation (summaries, drafts, questions)	Supports resource creation and elaboration; can increase engagement and study efficiency	Plagiarism/academic integrity; reduced critical thinking; bias in outputs	Explicit citation rules; process-based assessment; require source checking and originality criteria; prompt transparency
Personalization / recommendation (adaptive pathways)	Planning + motivation: tailored resources can sustain engagement and persistence	Filter bubbles; equity concerns; opaque recommendations	Ensure diverse resources; monitor access; explain recommendation logic; teacher oversight for fairness
Simulations / visualization support (earth/biology scenarios)	Supports inquiry and conceptual exploration; may aid monitoring through scenario testing	Lack of scientific accuracy; missing visual fidelity; false certainty	Use validated simulations when possible; triangulate with textbooks/labs; require hypothesis-evidence-conclusion structure
Governance / training (policies, classroom norms)	Creates conditions for responsible SRL: clear expectations, ethical use, and scaffolding routines	Over-restrictive policies may push hidden use; under-regulation increases misuse	Co-design rules with learners; teach AI literacy; align assessments with reasoning and verification tasks

For LES, a responsible integration should privilege inquiry-oriented tasks (hypothesis-evidence-conclusion), lab report justification, and source triangulation. GAI can be used to support planning (for example, creating investigations), generate different explanations to be evaluated, and provide feedback to help improve. Students should be required to document prompts and sources, verify claims against trusted references, and explain reasoning in their own words. Teacher mediation is still necessary to make sure students understand what they are learning, correct any misunderstandings, and continue to develop their ability to argue scientifically. Finally, the review confirms that teaching practices are changing. Al is being used more and more often to plan lessons, create content, and support reflective tasks [10, 8, 17]. However, some authors [2, 6] say that teachers need to keep learning. Research by Tao et al. (2025) shows that there is a growing interest in personalized learning and using technology to automate certain assessments. However, it's important to balance this with teaching and ethical considerations to ensure that learning remains meaningful and not just focused on data and productivity.

5. ORIGINAL CONTRIBUTION OF THIS REVIEW

This review has four original contributions. First, it introduces a clear analytical framework that links GAI functional use types to SRL components (Table 5 and Figure 3). This framework enables a structured comparison beyond simple narrative summaries. Second, it uses vote counting to measure the evidence (Figure 2) and frequency synthesis to measure the frequency of SRL components (Table 5 and Figure 4). This makes patterns visible despite the differences between them. Third, it makes it clear that a lot of the current evidence is moderate to low strength (Table 6). This shows where claims are strong versus claims based on how things work. Fourth, it suggests a way of thinking about problems (Table 7) that matches teaching methods and safety measures with GAI use that supports SRL. This way of thinking translates proof into practical design ideas.

6. CONCLUSIONS

This systematic review indicates that generative Al tools can support self-regulated learning in secondary Life and Earth Sciences when they are used as scaffolds rather than as answer generators. In other words, these tools are more useful when they help students think, organize their work, and reflect on their learning, instead of giving ready-made answers. Across the 12 included studies, the most frequently addressed SRL component is self-reflection and self-assessment (75%), followed by monitoring (67%), planning and time management (58%), and motivation and engagement (58%) (Table 5). This shows that generative Al can play a positive role in several important parts of the learning process. However, the reviewed studies also show that the use of these tools is not always positive or easy. Most studies report important constraints and risks, including over-reliance on Al, inaccurate outputs or hallucinations, reduced conceptual engagement, and concerns about academic integrity (Figure 2 and Table 4). These limits show that generative Al cannot be seen as a simple solution for learning. If students use it without guidance, they may trust incorrect information, think less deeply, or depend too much on the tool. For this reason, the educational value of generative Al depends strongly on pedagogical mediation. Tasks must require students to explain their ideas, justify their answers with evidence, and verify the information they receive. Learners must remain active and responsible for their own reasoning during the learning process. For Life and Earth Sciences, some uses appear especially promising. Generative Al can help students plan inquiry activities, suggest different explanations that need to be discussed and evaluated, and provide formative feedback during report writing. These uses can support students step by step and help them improve their work. At the same time, implementation should be accompanied by Al literacy instruction, explicit classroom norms, and assessment designs that reward scientific argumentation and source triangulation. This means that students need to learn not only how to use Al tools, but also how to question them, check them, and use them in a responsible way.

Finally, future research should prioritize long-term classroom studies in secondary Life and Earth Sciences with objective SRL measures, such as trace data and validated SRL instruments, as well as transparent reporting of prompts, activities, and teacher roles. More research is needed to better understand how generative Al affects students over time, under real classroom conditions, and with different teaching approaches. This would help provide a clearer view of both the benefits and the limits of these tools in science education.

NOMENCLATURES

LES	Life and Earth Sciences
GAI	Generative Artificial Intelligence
AI	Artificial Intelligence
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
SRL	Self-Regulated Learning

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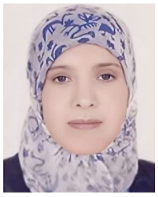
BIOGRAPHIES

Name: **Moncef**
Surname: **Belmajdoub**
Birthday: 08.10.1999
Birthplace: Agadir, Morocco
Bachelor: Teaching Life and Earth Sciences, Higher Normal School, Mohammed V University, Rabat, Morocco, 2021
Master: Teaching Life and Earth Sciences, Higher Normal School, Cadi Ayyad University, Marrakesh, Morocco, 2023
Doctorate: Student, Laboratory of Education, Science, and Technology, Higher School of Education and Training, Hassan I University, Settat, Morocco, Since 2024
Scientific Position: Life and Earth Sciences Teacher, Agadir, Morocco, Since 2023
Research Interests: Didactics of Sciences, Pedagogy, Engineering Training, Educational Technology, Life and Earth Sciences
Scientific Publications: 1 Paper

Name: **Aafaf**
Surname: **Essedaoui**
Birthday: 23.05.1972
Birthplace: Youssoufia, Morocco
Bachelor: Animal Biology, Faculty of Sciences, Chouaib Doukkali University, El Jadida, Morocco, 1993
Master: Marine Sciences, Department of Biology, Faculty of Sciences, Chouaib Doukkali University, El Jadida, Morocco, 1994
Doctorate: Biology, Specialization: Environmental Sciences, Option: Ecophysiology, Faculty of Sciences, Chouaib Doukkali University, El Jadida, Morocco, 2000
Scientific Position: Prof., Regional Centre for Education and Training Professions, Casablanca-Settat, El Jadida, Morocco, Since 2019
Research Interests: Engineering Training, Didactics of Sciences, Pedagogy, Educational Technology, Biology
Scientific Publications: 30 Papers



Name: **Sabah**
Surname: **Belaaouja**
Birthday: 17.09.1973
Birthplace: Sidi Kacem, Morocco
Bachelor: Animal Biology, Faculty of Sciences, Ibn Tofail University, Kenitra, Morocco, 1999
Master: Didactics of Sciences, Faculty of Educational Sciences, Mohammed V University, Rabat, Morocco, 2003
Doctorate 1: Biology, Faculty of Sciences, Ibn Tofail University, Kenitra, Morocco, 2011
Doctorate 2: Didactics of Sciences, Faculty of Educational Sciences, Mohammed V University, Rabat, Morocco, 2023
Scientific Position: Prof., Didactics of Sciences, Department of Didactics and Science Education, Higher School of Education and Training of Berrechid, Hassan I University, Settat, Morocco, Since 2019
Research Interests: Didactics of Sciences and Technology, Training Engineering, Assessment Pedagogy, Intelligent Artificial
Scientific Publications: 23 Papers