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	JIF	= 1.500	SJIF (Morocco)	= 6.004	OAJI (USA)	= 0.350

SOI: [1.1/TAS](#) DOI: [10.15863/TAS](#)
International Scientific Journal
Theoretical & Applied Science

p-ISSN: 2308-4944 (print) e-ISSN: 2409-0085 (online)

Year: 2026 Issue: 05 Volume: 157

Received: 15.05.2026
Accepted/Published: 30.05.2026 <https://T-Science.org>



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FROM AUTOMATION TO AUGMENTATION: A HUMAN-CENTERED FRAMEWORK FOR RESPONSIBLE GENERATIVE AI IN EDUCATION

Abstract: Generative artificial intelligence is changing how learners seek explanations, draft ideas, receive feedback, revise texts and complete academic tasks. Institutional responses tend to fall between two limited positions: viewing the technology mainly as a tool for automation and productivity, or mainly as a risk to academic integrity and independent learning. This article argues both views are incomplete, as the key educational question is whether generative AI helps or hurts human learning. The research employs a qualitative conceptual approach to differentiate between automation and augmentation, and to develop a human-centered model for responsible use in education, based on Self-Determination Theory. The discussion produces five key observations: that the responsible use of technology is a pedagogical matter, not a matter of tool presence; that augmentation has value when it supports autonomy, competence, and relatedness; that cognitive effort must be protected; that academic integrity involves process-sensitive assessment; and that institutional governance must link policy, pedagogy, professional development, and learner literacy. This article proposes a Human-Centered Augmentation Framework, which is oriented around six dimensions: pedagogical alignment, learner agency, cognitive effort, transparent process, relational teaching presence, and institutional accountability. This framework offers a practical way for educators and institutions to distinguish between learning-supportive and learning-substitutive use.

Key words: generative AI; human-centered education; learner agency; academic integrity; assessment design; self-determination theory.

Language: English

Citation: Al Souleiman, I., & Al Souleiman, H. (2026). From automation to augmentation: a human-centered framework for responsible generative AI in education. *ISJ Theoretical & Applied Science*, 05 (157), 332-339.

Soi: <https://s-o-i.org/1.1/TAS-05-157-20> **Doi:** <https://dx.doi.org/10.15863/TAS.2026.05.157.20>
Scopus ASCC: 3304.

Introduction

Digital systems that produce explanations, summaries, outlines, feedback, examples and long academic texts are increasingly shaping education. These systems are not only changing the way students do assignments; they are also changing the way teachers think about learning, assessment, authorship and responsibility. Therefore, the swift arrival of generative artificial intelligence has presented a major challenge to educational institutions. The question is not just whether such technologies should be accepted or rejected. The deeper question is how education can

take advantage of them without compromising the human capacities education is supposed to develop.

The title of this article strikes a chord with the central argument: education needs to shift from automation to augmentation. Automation is the transfer of work from people to systems. Automation in education might mean writing answers, summarizing readings, creating lesson materials, editing student work, or providing feedback with limited human input. Automation may be useful in some administrative and support functions, but becomes problematic where the automated task is the learning task itself. If the goal is for students to learn

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how to argue, interpret, reason ethically, and understand disciplines, then substituting these processes for automated production defeats the purpose of education.

Augmentation has a different logic. It uses technology to enhance human capabilities, while keeping the learner intellectually engaged and responsible. An augmentative use can help students compare explanations, receive formative feedback, find weaknesses in their reasoning, organize their ideas, or test alternate interpretations. It can also help teachers develop learning materials, give personalized support and pinpoint areas where students require more guidance. In all instances, the technology supports the learner, but it does not eliminate the learner's responsibility to understand, judge, explain, and revise.

The distinction between automation and augmentation is important because the current debate about education is often too general. Some of the discussions are around efficiency, innovation, access. Others focus on detection and prohibition of plagiarism. Both areas are needed, but neither is enough. Technology can reduce learning and improve efficiency. A policy might prohibit misuse, but it would not teach responsible use. An enforcement system can support the presence of academic integrity, but cannot create it. These frictions point to the need for a human-centric paradigm to evaluate generative artificial intelligence on the basis of its effect on learning rather than on its technical capacity.

Previous research on artificial intelligence in higher education has shown that technological development often outpaces pedagogical reflection. Zawacki-Richter et al. found that research in this area tended to focus on technical systems, prediction, profiling and automation, with less attention to perspectives centered on educators [14]. Crompton and Burke reviewed the status of artificial intelligence in higher education and found that the field is growing in teaching, learning, assessment and institutional practice, which validates the need for clearer educational frameworks, not isolated technical adoption [3]. The imbalance is still substantial. Many institutions are still responding with emergency rules, tool restrictions or academic integrity warnings, with less attention to curriculum redesign, student agency, teacher judgment and assessment reform.

Recent work has also demonstrated that the opportunities and risks of generative AI are closely intertwined. Kasneci et al. referred to possible benefits such as tailored assistance, language support and feedback, but also concerns about bias, misinformation, dependency and academic integrity [8]. This field has been described by Hsu and Ching as a dynamic frontier that requires careful educational adaptation [5]. These studies argue that the same technology can be used to either support or undermine learning. A student might employ a system to

understand a difficult idea, or to sidestep the idea entirely. It might be used by a teacher to improve learning design, or to standardize teaching in ways that reduce professional judgement.

The research gap that this article attempts to fill is the absence of a clear conceptual framework linking responsible use of generative artificial intelligence to human-centred learning, learner motivation, academic integrity and governance of institutions. The literature identifies significant risks and benefits, but practical decision making is often fragmented. Teachers need more than a sweeping statement about innovation or integrity. They need a pedagogical logic that helps them decide when a particular use supports learning and when it replaces learning. Absent such a logic, institutions may promulgate inconsistent rules, rely excessively on detection, or promote the use of technology without sufficient safeguards.

The aim of this article is to develop a human-centered framework for responsible generative AI in education that shifts the focus from automation to augmentation. There are four objectives. The article first clarifies the pedagogical difference between automation and augmentation. Second, we use Self-Determination Theory to explain why autonomy, competence, and relatedness are fundamental criteria for responsible use. Third, it critically discusses the impact of generative artificial intelligence on learning, assessment, academic integrity, and institutional governance. Fourth, it provides a practical framework which can inform educators, curriculum designers and academic leaders.

The following three research questions serve as the guide for the study:

RQ1: How might we comprehend the difference of automation and augmentation in relation to responsible generative artificial intelligence in education?

RQ2: What human-centered principles should guide the educational use of generative artificial intelligence to support learner agency, competence, and academic integrity?

RQ3: How educational institutions can implement an augmentation approach to their curriculum, assessment and governance practices?

In doing so, the article contributes to the literature by posing the question of responsible use as a question of human development, not technological permission. It argues that educational institutions should not only be asking if students may use generative artificial intelligence. They should ask what students still need to think, understand, question, explain and demonstrate when they use it.

Theoretical Framework: Self-Determination Theory

The theoretical underpinning of this paper is Self-Determination Theory, which offers the conditions that foster high-quality motivation, agency,

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and meaningful engagement for learners. Ryan and Deci argued that human motivation is affected by three basic psychological needs, namely autonomy, competence and relatedness [11]. Autonomy is the experience of acting with meaningful choice and personal endorsement. Competence is the experience of becoming able and effective. Relatedness is about connection, recognition, and belonging in a social setting. These needs are fundamental in education, because learning is not just about acquiring information. And it is the development of confidence, judgment, identity, responsibility and involvement.

Self-Determination Theory is particularly useful in distinguishing between automation and augmentation. Automation can enhance speed, decrease workload, and deliver polished outputs, but it doesn't necessarily support autonomy, competence, and relatedness. Sometimes it can even weaken them. If students use technology to produce work they do not understand, they may have an output but lose competence. If students use systems covertly because rules are not clear then autonomy is related to avoidance rather than responsible choice. If the use of technology results in less meaningful interaction with teachers and students, then relatedness may suffer.

However, augmentation can support the three psychological needs if carefully designed. It supports autonomy when students are taught how to make informed decisions about technological assistance. It can support competence when students are provided with explanations, opportunities to practice and formative feedback which increases understanding. It can support relatedness when technology allows teachers to provide more individualized support or when it helps learners engage more deeply with the academic tasks. The educational question then is not whether the technology is present but whether its use reinforces the active role of the learner.

This theory also helps explain why a purely control-based response to generative AI is insufficient. Institutions need rules for academic integrity, but ethics does not come only from rules. If students experience policy only as surveillance or punishment, they may comply externally without developing responsible judgment. Ryan and Deci argue that the more an environment supports autonomy, competence and relatedness, the deeper the internalization is likely to be [11]. Hence responsible use requires clear boundaries and meaningful educational guidance.

This view is supported by research on self-regulated learning. Zimmerman defined self-regulated learners as active participants who use metacognitive, motivational and behavioral strategies to guide their learning [15]. Generative AI can support self-regulation through planning, questioning, revising, and reflecting. However, it can also undermine self-regulation when students rely on it as a crutch to complete these activities without actively engaging in

them. The theoretical implication is clear. The responsible use should be judged by the role of the learner in the process. The more the learner plans, evaluates, explains, revises, the more likely the use is to be augmentative. The more the system performs these functions in lieu of the learner, the more it is likely to be substitutive.

Methodology

This article adopts a qualitative conceptual and analytical methodology grounded on academic literature. There is no empirical data collection and no statistical claims are made. This is appropriate, since the field is evolving rapidly and needs clearer concepts before reliable institutional practices can be designed, evaluated and compared. The goal is not to measure student behavior in one context, but to develop a theoretically driven framework that can guide future research and practice.

The conceptual analysis was carried out in three phases. We first reviewed the relevant academic literature on artificial intelligence in education, human-centered educational technology, assessment, academic integrity, learner motivation, and self-regulated learning in order to identify recurring themes and tensions. The second step was to interpret these themes in light of Self-Determination Theory, using autonomy, competence and relatedness as criteria for educational value. Third, the analysis was synthesized into a Human-Centered Augmentation Framework that differentiates between learning-supportive and learning-substitutive uses of AI.

The methodology is both descriptive and critical. It does not take for granted that innovation is necessarily for the good, or that educational risk justifies rejection. Instead, it measures generative artificial intelligence by its impact on human learning. This matter because the same system can produce different educational outcomes depending on task design, teacher guidance, student intention, and institutional policy.

The conceptual methodology is limited in that it does not directly provide empirical evidence from students and teachers. Its value is, however, that it clarifies the categories needed for future empirical work. Institutions need a coherent way to define responsible use before they can measure it. The aim of this article is to address this need by proposing a framework that can later be tested, adapted and operationalized in different disciplines and educational levels.

Literature Review and Research Gap

Research on artificial intelligence in education has proliferated in a number of areas, including adaptive learning, intelligent tutoring, learning analytics, automated feedback, assessment, ethics and institutional governance. Popenici and Kerr argued that artificial intelligence would affect teaching and

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learning in higher education, while highlighting the importance of institutional readiness and ethical reflection [10]. Later, Zawacki-Richter et al. pointed out that although research in this field has been growing, educator perspectives are often underrepresented [14]. Crompton and Burke have also noted that AI in higher education has become a broad field that intersects with teaching, learning, assessment, and institutional practice, reinforcing the need for responsible educational frameworks [3]. Holmes and Tuomi also pointed out that artificial intelligence in education should be understood from the viewpoint of technological practice and educational purpose [4]. Hwang et al. also identified the major research issues and challenges for artificial intelligence in education, including the need to connect technical innovation with meaningful learning roles [6]. These studies highlight an ongoing problem: educational technologies tend to be studied in terms of their technical functions before their pedagogical meaning is fully developed.

Human-centered methods address this issue by putting learners, teachers and educational values at the center of design. Yang et al. argued that human-centered artificial intelligence in education should reveal the human conditions that are often hidden behind technical systems [13]. This matter because education cannot be reduced to prediction, personalization or efficiency. Learning involves uncertainty, dialogue, identity formation, ethical judgment and the slow development of disciplinary thinking. A human-centered approach therefore questions not only what systems can produce, but what kinds of human development they enable or restrict.

Generative AI makes things more difficult because it's very flexible. Kasneci et al. [8] identified opportunities such as individualized support and language assistance, and challenges such as accuracy, bias, dependency, and academic integrity. Hsu and Ching have insisted that continuing educational modifications are needed in the area [5]. The core problem is that one technology can do many different things. It can help you brainstorm, explain a concept, revise grammar, create a study plan, produce an argument, or generate a full assignment. The same system can be used responsibly or irresponsibly, so policy cannot be based on technology alone.

Some of the biggest concerns are with assessment and academic integrity. Balducci [2] suggested that assessment in human-centered education should focus on authenticity, collaboration and process rather than merely on final products. This is particularly relevant as polished outputs may no longer be reliable evidence of independent learning. Johnston et al. illustrated the complexity of student perspectives on generative artificial intelligence in higher education, suggesting that institutions need clear guidance rather than simple assumptions about

student misuse [7]. Khosravi et al. also stressed the importance of explain ability in educational systems, as learners and teachers need to know what effect technological support has on decisions, feedback and outcomes [9].

Literacy is another key area. Responsible technology use is more than access. Students need to learn about limitations, errors, bias, quality of evidence, ethical boundaries and the difference between support and substitution. Tzirides et al. argued that the combination of human and artificial intelligence can support literacy when learners are guided to evaluate, question and collaborate with systems rather than passively relying on them [12]. This is in line with the main argument of this article: the educational value depends on the active human engagement.

However, despite these contributions, the research gap is clear. While the literature discusses benefits, risks, ethics and assessment challenges, it does not necessarily provide a practical conceptual distinction between automation and augmentation. Many studies describe what generative artificial intelligence can do, but fewer describe how educators can judge if a particular use strengthens or weakens learning. There is also a need to connect responsible use to learner motivation, academic integrity and institutional governance. Recent scholarship has stressed the need to move from simply automating to augmenting in a human-centered way that safeguards learner agency, judgment and academic responsibility [1]. In this direction, the present article suggests a structured framework for educational decision making.

Analysis: From Automation to Augmentation

Automation and augmentation are not just technical categories. They embody two different educational logics. Automation is about shifting work from people to systems. In education, this could mean generating answers, producing summaries, revising text, grading responses or generating learning materials. Some automation can be useful, particularly for routine administrative functions or lower-level support. But when the task being transferred is central to the learning outcome, automation becomes educationally risky.

For example, if an assignment is intended to encourage critical reading, automated summarization may defeat the purpose of the assignment if students do not read, interpret, or evaluate the original text. If the task is to develop argumentation, the reasoning process can be replaced by the automated production of essays. Where the assignment is designed to encourage reflective judgement, automated reflection can create the illusion of personal insight without any real self-examination. In these cases, the problem is not the technology itself. The problem is that the cognitive role of the learner has been displaced.

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Augmentation is a different logic. It uses technology to support rather than replace the activity of the learner. A student might use generative support to compare possible explanations, test the clarity of an argument, identify gaps in reasoning, or receive suggestions for revision. A teacher may use it to develop examples, tailor materials or create formative activities. In each case, the human remains the source of judgment and meaning. The tool may help, but the learner still has to think, decide, explain and revise.

Feedback is a good example. The automatic feedback might correct a sentence or yield a revised paragraph. This can lead to a better surface quality, but not necessarily to a more competent learner. Augmentative feedback, on the other hand, explains to the student why change is needed, asks the student to make choices, and invites reflection. It makes feedback a process of learning not a replacement service. The same is true for research support. A system can suggest potential themes, but the student still has to consider evidence, select relevant literature, and construct a defensible argument.

Assessment also depends on the distinction between automation and augmentation. When polished outputs can be produced rapidly, product-only assessment becomes more vulnerable. But this does not mean that writing should be abandoned or that institutions should rely only on closed-book exams. A human-centered approach demands assessment designs that make learning visible. These could be annotated drafts, oral explanations, reflective statements, staged submissions, in-class applications, and teacher-student dialogue. These approaches do not eliminate all risk, but they do improve the connection between assessment and demonstrated understanding.

The ethical question is not about students using technology but rather are they still accountable for learning. The learner does not understand the answer but a fluent answer may seem academically mature. This is a decoupling of performance and competency. Education must therefore protect the relation of expression to understanding. Students should be able to justify their claims, defend their choices, identify limitations, and revise based on critique. These abilities should be made more visible, not less visible, through responsible use.

Findings

Finding 1: Pedagogical Function – Not Tool Presence – Drives Responsible Use

The first finding is that responsible use depends on what the technology does in a learning task. The same tool can either support or undermine education, depending on how it is used. If a student uses generative support to generate possible counter-arguments and critically evaluates them, the use may be conducive to learning. If the student uses it to generate a final argument without understanding, the

use substitutes for learning. Therefore, institutional policy should not be a binary classification of use at the tool level into allowed or prohibited. It should categorize use at the task level.

This finding answers RQ1 by indicating that the learner's role defines automation and augmentation. Automation substitutes the intellectual effort of the learner. Augmentation supports the learner's intellectual work.

Finding 2: Augmentation Supports Autonomy, Competence, and Connection

The second finding is that responsible educational use should foster autonomy, competence, and relatedness. Autonomy is fostered when students understand their choices and are guided to use technology intentionally. It supports competence when students are more able to explain, apply and improve their work. It supports relatedness when technology supports meaningful interaction with teachers and peers, rather than diminishing it.

RQ2 is answered by this finding, which provides human-centered criteria for responsible use. Transparency alone is not enough. A student may use a system in a manner that is transparent yet still reduces learning. Responsible use must contribute to human development.

Finding 3: The Need to Protect Cognitive Effort

Finally, our third finding is that cognitive effort is no barrier to education. It is a part of education. Learning is often a matter of uncertainty and revision, of difficulty and struggle. Generative systems may reduce unnecessary barriers but should not detract from the intellectual effort through which competence develops. The trick is to distinguish between unproductive difficulty and productive learning effort.

This finding is significant because efficiency is a common argument in the world of technology. In education, however, faster completion does not necessarily mean better learning. If students arrive at an answer without going through the reasoning, much of the educational value of the task is lost.

Finding 4: Evaluation Must Be Process Sensitive for Academic Integrity

Fourth, academic integrity cannot be based primarily on detection or evaluation of the end product. Detection systems can be faulty, and over-reliance on them can create a culture of suspicion. A more useful response is to create assessments with process evidence. Teachers can use planning notes, revision logs, oral defense, reflective commentary and contextual application to assess students' understanding of their work.

This answers RQ3 with the fact that integrity should be embedded in assessment design. It is not to be considered a punishment only after submission.

Finding 5: Institutional Governance Should Link Policy, Pedagogy, and Professional Development

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The fifth is that responsible integration requires institutional coherence. Policies need to outline what is acceptable and unacceptable, but they also have to be supported by teacher training, student literacy, curriculum design and assessment reform. When policy is unclear, teachers are unsupported and students are only warned, responsible use is inconsistent.

This finding speaks to RQ3 underlining the fact that responsible use is an institutional ecosystem. It cannot be a question only of individual teachers or individual student choices.

A Human-Centered Augmentation Framework

Based on the analysis, this paper proposes a Human-Centered Augmentation Framework for responsible generative artificial intelligence in education. The framework is composed of six interconnected dimensions.

The first dimension is pedagogical fit. Each use should be linked to a specific learning outcome. If critical analysis is the goal, the technology should facilitate question asking and evaluation, not the production of the final analysis. When developing writing is the goal, the technology can help with feedback and revision, but the student must drive the argument, structure, and evidence. Pedagogical alignment begs a simple question: does this use support the purpose of the task?

The second dimension is learning agency. Students need to be taught how to make informed decisions about technology assistance. This includes understanding limitations, verifying accuracy, recognizing bias and documenting use where required. Agency is not absolute freedom. It is a guided responsibility. Students need to understand not just what is permissible but the reasons why some uses advance learning and others impede it.

The third dimension is cognitive effort. Learning tasks should demand students to think, explain, revise and apply. Technology may reduce mechanical burdens, but should not remove the central intellectual challenge. Educators should ask: what does the learner still have to do that demonstrates learning? If the answer is not clear, the task may need to be redesigned.

The fourth dimension is transparent process. Students should be able to explain how they used the support, what they accepted or rejected, and how their own thinking changed. Transparency should not be viewed only as compliance. It should connect to reflection and learning. A brief process statement, revision log or oral explanation can help to make student understanding visible.

Relational teaching presence is the fifth dimension. The generative support offered should not lessen the role of teachers. Teachers are still needed for interpretation, care, ethical guidance, disciplinary standards and feedback that recognizes the learner as

a person. Technology may offer constant support, but it cannot replace the educational relationship.

The sixth dimension is institutional responsibility. Institutions need to provide clear policies, professional development, student literacy programs, assessment guidance and mechanisms for review. Accountability also means attention to equity, accessibility, privacy and consistency. Responsible use should be a distributed activity across the institution rather than an isolated decision at the course level.

Taken together, these six dimensions offer a practical means to go from automation to augmentation. Technology is not dismissed by the framework. Instead, it asks whether technology use improves human learning. It can be used in course design, assessment planning, student guidance and institutional policies.

Discussion

The proposed framework contributes to the ongoing educational debate by shifting the focus from tool-centered questions to learning-centered questions. Some institutional responses begin with the question of whether students should be permitted to use generative artificial intelligence. The article suggests that the better first question is what kind of learning the task should promote. Once that is clear, educators can determine what types of technology support are suitable.

This is important because it is impossible to determine what responsible use is in the abstract. It depends on discipline, level, task purpose, assessment method and learner readiness. What is appropriate for use in an early brainstorming activity may not be appropriate for a final assessment. A use that supports language clarity may be acceptable as long as the student is responsible for ideas and evidence. If the assessed outcome is argumentation, then a use that produces the central argument might be unacceptable. The framework helps educators to make these distinctions more explicit.

The framework also questions the assumption that efficiency is always educationally positive. Automation is useful in many work areas because it saves time and labor. But in education, some kinds of effort are not wasted. Learning to read difficult texts, build arguments, revise unclear writing and respond to critique are developmental processes. If these processes are removed, the result may be faster output but weaker learning. Therefore, responsible educational technology should lower barriers where they are unnecessary and maintain the effort that builds competence.

The framework also does not make difficulty an end in itself. Some difficulty is not useful. Students may encounter language barriers, disability, limited prior preparation, low confidence or unequal access to academic support. Generative systems may help to

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reduce some of these barriers by providing explanations, examples and opportunities for practice. Human-centered augmentation does not mean maintaining all struggle. It means keeping meaningful intellectual work intact while reducing barriers to participation.

The framework also has implications for academic integrity. Traditional models of integrity tend to emphasize the originality of the final product. Generative artificial intelligence complicates this model because final products may no longer offer reliable evidence of independent learning. Institutions should thus pay more attention to authorship as accountable learning. Students should be able to show that they own their thinking. They can describe their process, justify their claims, and demonstrate how they altered their work.

Professional development is a must for teachers. Educators need support in redesigning assignments, communicating expectations, and evaluating evidence of process. Without such support they may find generative AI to be largely an added burden. Institutions should offer practical guidance, shared rubrics, examples of acceptable use, and time to redesign assessments. Teachers also require institutional support for the implementation of academic standards.

The curriculum needs to integrate student literacy. Students should not have to infer responsible use from piecemeal rules. They need direct instruction in ethical use, critical appraisal, quality of evidence, acknowledgement practices, and the distinction between assistance and substitution. Literacy needs to be established early and reinforced across programs. Responsible use is not a single policy message. It is a graduate skill.

Conclusion

Generative AI is taking education to a crossroads between automation and augmentation. Automation may produce outputs more quickly, but it can also

erode the human capacities that education is meant to foster. Augmentation is a technology to support understanding, reflection, agency, feedback and participation but leaves the responsibility for judgment and meaning with the learner. The argument of this article is that the responsible way forward is neither a simple ban nor unrestricted adoption, but a human-centered framework that assesses the technology based on its impact on learning.

The article showed that responsible use should promote autonomy, competence, and relatedness using Self-Determination Theory. It also argued that academic integrity should be built through process-sensitive assessment and learner literacy rather than detection. The proposed Human-Centered Augmentation Framework is composed of six dimensions: pedagogical alignment, learner agency, cognitive effort, transparent process, relational teaching presence, and institutional accountability. These dimensions provide a practical framework for educators and institutions to integrate generative artificial intelligence without sacrificing educational purpose.

The article's main contribution is a clear distinction between learning-substitutive and learning-supportive use. When technology helps students think more deeply, act more consciously, revise more effectively, and demonstrate understanding more clearly, it becomes educationally responsible. It is educationally risky when it creates the illusion of learning while diminishing the learner's active role. The framework can be empirically tested in future research across different disciplines, education levels and institutional settings. Future studies could explore students' sense-making of augmentation, teachers' redesign of assessment and institutions' coherent governance. The core principle is straightforward: good educational technology should not replace the learner. It should make the learner more capable, more reflective and more responsible.

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