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Generative AI Personalization and Learner Autonomy: A Conceptual Framework for Agency-Preserving Adaptive Learning

Hilalludin^{1*}, Muzanni²¹Universitas Alma Ata Yogyakarta, Indonesia²University of Science and Technology, Yaman

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Correspondence

E-mail: hilalluddin34@gmail.com *

A B S T R A C K

This conceptual review develops an agency-preserving framework for generative artificial intelligence (GenAI)-supported adaptive learning. Its starting problem is that personalized assistance and improved performance during AI use do not necessarily demonstrate greater learner autonomy. The analysis critically compares selected theoretical accounts, published educational studies, reviews, and human-centred governance guidance relevant to personalization, self-regulation, and human responsibility. It distinguishes conversational responsiveness from personalization and from instructional adaptation based on evidence of learners' needs. The proposed conditional loop connects diagnostic fit, graduated assistance, meaningful learner choice, verification of generated information, independent-transfer checks, and educator accountability. Contrasting published findings indicates why assisted task completion must be evaluated separately from learning that persists when support is withdrawn. The contribution is a testable conceptual decision criterion, not a validated intervention or estimate of effectiveness. Because the review did not use a documented exhaustive search or formal study appraisal, the conclusions are interpretive and context-bounded. Future research should examine the loop's mechanisms, moderating conditions, and measurable indicators of independent reasoning and self-regulated learning.

Abstrak

Kajian konseptual ini mengusulkan kerangka pembelajaran adaptif berbasis kecerdasan buatan generatif (GenAI) yang menjaga agensi peserta didik. Persoalan utamanya ialah bahwa personalisasi dan peningkatan kinerja ketika AI digunakan tidak otomatis menunjukkan kemandirian belajar. Kajian ini membandingkan secara kritis argumentasi teoretis, tinjauan pustaka, hasil penelitian pendidikan, dan panduan tata kelola yang dipilih karena relevansinya terhadap personalisasi, regulasi diri, dan tanggung jawab manusia. Analisis membedakan respons percakapan, bantuan yang dipersonalisasi, dan adaptasi yang didasarkan pada bukti kebutuhan belajar. Kontribusi yang diajukan berupa siklus bersyarat yang menghubungkan diagnosis kebutuhan, bantuan bertahap, pilihan peserta didik, verifikasi informasi, pengujian kemampuan mandiri, dan akuntabilitas pendidik. Sintesis menunjukkan bahwa keberhasilan tugas dengan bantuan GenAI perlu dibedakan dari transfer pengetahuan tanpa bantuan. Kerangka ini merupakan proposisi konseptual yang belum diuji secara empiris, bukan hasil penelusuran literatur sistematis atau estimasi efektivitas. Penelitian berikutnya perlu menguji mekanisme, batasan konteks, dan indikator kemandirian belajar dalam berbagai desain pembelajaran.

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1. Introduction

Generative artificial intelligence (GenAI) can produce explanations, feedback, worked examples, and conversational prompts that respond immediately to students' requests. These affordances have

made large language models relevant to instructional design, but their educational usefulness depends on how generated content is incorporated into learning activity rather than on fluency alone [1], [2], [3], [4]. Recent reviews describe opportunities for individualized feedback and flexible participation while also identifying reliability, assessment, and human-control concerns [5], [6], [7]. For educators, the unresolved issue is therefore not simply whether GenAI can make materials more accessible, but whether adaptive assistance can be designed to leave learners progressively more capable of reasoning without that assistance.

The difference between assisted task performance and independent learning is especially consequential. Experimental research has reported improvements in students' performance while particular forms of GenAI assistance are available, yet benefits during practice need not persist when that assistance is withdrawn. Bastani and colleagues' study of secondary-school mathematics offers a particularly salient example of this distinction, whereas experimental work on creative problem solving illustrates that benefits can vary by task and outcome [8], [9]. A meta-analysis of experimental studies likewise provides a broader picture of heterogeneous educational effects, without establishing that every use of ChatGPT promotes learner autonomy [10]. An autonomy-centred account must therefore specify the outcomes and conditions under which immediate assistance constitutes support rather than substitution for thinking.

This problem requires a sharper distinction among three terms often used interchangeably. Conversational responsiveness means that an AI tool generates a reply to a prompt; personalization means that the reply or learning pathway is tailored to a user characteristic or request; and educational adaptation requires a justified adjustment based on evidence of the learner's understanding, progress, or need. Work on personalized learning and adaptive systems demonstrates that different routes to personalization can be combined, while a hybrid human-AI approach places teachers and learners within the decision process [11], [12], [13], [14]. The distinction matters because a personalized explanation may be convenient but still fail to create an instructional feedback loop or opportunities for increasingly independent performance.

Prior scholarship supplies important components of a human-centred response, but those components address partially different problems. Molenaar proposes hybrid human-AI learning technologies that preserve human participation in regulation and decision-making [14]; Brod discusses the combination of multiple approaches to educational personalization [11]; and Haro-Sarango offers a conceptual human-AI pedagogical-agency perspective linking learning, cognition, and ethics [15]. A scoping review explicitly joins cognitive offloading and learner agency, identifying a related tension in higher education [16]. These contributions mean that the mere coexistence of personalization, autonomy, and ethical oversight is not novel. A narrower unresolved conceptual question is how an educator might distinguish assistance that appropriately adapts to learners from assistance that progressively displaces their epistemic choices and independent transfer.

Evidence also cautions against a one-directional account of GenAI use. A randomized trial of GenAI-supported self-regulated learning in schools investigated distinct motivational, regulatory, and learning outcomes rather than treating them as interchangeable [17]. Work on questioning behaviour and perceived self-regulation further suggests that learners' interaction strategies and cognitive offloading deserve separate scrutiny, although observational or perceived outcomes do not establish causal improvement [18], [19]. Structured peer-assessment and mathematical scaffolding studies indicate that the instructional arrangement surrounding AI can differ materially from unrestricted answer generation [20], [21]. This variation motivates the need for boundary conditions instead of a universal claim that more or less AI assistance is always educationally preferable.

The article develops an interpretive conceptual analysis rather than a systematic evidence review. In line with methodological accounts of conceptual scholarship, it clarifies constructs, compares explanatory perspectives, and formulates propositions that may subsequently be tested rather than

estimating an effect or claiming representative coverage [22]. The analytic object is the published proposition about the relationship among AI assistance, learner regulation, instructional adaptation, and governance. Existing scholarship is used to examine convergences and tensions; differences between primary studies, literature reviews, theoretical models, and policy guidance are made explicit wherever they matter for the strength of a claim.

Four conceptual questions guide the analysis: (RQ1) What distinguishes GenAI-supported adaptation from generic conversational assistance and personalization? (RQ2) Through which plausible pathways might graduated AI assistance preserve or displace learner agency and self-regulated learning? (RQ3) Which contextual and ethical conditions constrain these pathways? (RQ4) What design decisions and future evaluation criteria follow from integrating these dimensions? The questions concern explanatory relationships and design propositions, not the prevalence of practices or the average causal effectiveness of GenAI across education.

The proposed contribution is an agency-preserving adaptive-learning loop: pedagogical assistance is matched to diagnosed need; the learner retains opportunities to select, question, and justify actions; support is gradually adjusted; and independent performance without AI is assessed separately from assisted performance. Teacher accountability, transparency, and equitable access qualify each step. This loop is more specific than a list of desirable principles because it introduces a conditional design test: assistance counts as autonomy-supportive only when it both responds to a learning need and protects meaningful opportunities for decision-making and independent transfer. This remains a conceptual proposition, not a validated causal model; its usefulness must be assessed against competing explanations and different educational settings [23], [24], [25].

2. Research Method

2.1. Research Design and Conceptual Questions

The article follows a critical, interpretive conceptual-review design. The purpose is to specify and relate constructs, compare competing explanatory claims, and propose conditional educational design principles. Unlike systematic reviews or meta-analyses, it does not estimate the frequency or pooled effect of an intervention. The unit of analysis is a published conceptual or empirical proposition, not a student, institution, database record, or AI application. The four RQs identified in the Introduction organized the analysis, while the distinction between AI affordances, learner processes, outcomes, and safeguards constrained interpretation [22].

Four predefined analytical dimensions framed comparison: (i) GenAI capabilities and instructional responsiveness; (ii) personalization versus evidence-responsive adaptation; (iii) autonomy, agency, and self-regulation as distinguishable learner processes; and (iv) human oversight and ethical governance. Table 1 defines these boundaries. These were deductive organizing dimensions selected to address the conceptual problem; they are not claimed as inductive themes discovered through formal qualitative coding or as search strings executed identically in bibliographic databases.

Table 1. A Priori Conceptual Dimensions and Analytical Boundaries

No.	Conceptual Dimension	Analytical Boundary
1	GenAI capabilities	Prompt-conditioned explanation and feedback; distinguish generated content from measured instructional effects.
2	Personalization and adaptation	Tailoring to learner needs; adaptation additionally requires learner evidence, adjustment criteria, and feedback.
3	Learner agency and SRL	Volitional choices, goal regulation, monitoring, reflection, and independent transfer are related but distinct.
4	Human-centred governance	Privacy, contestability, equity, transparency, and educator accountability constrain appropriate AI support.

The dimensions in Table 1 guide what can be compared and which inferences must remain separate. In particular, the ability of an AI model to generate individualized content is not evidence that the learner has become more autonomous. Such a learner outcome would require appropriately defined indicators and direct observation. The table therefore functions as a conceptual specification, not as a PRISMA search protocol.

2.2. Documentary Corpus and Source Relevance

The documentary basis is an intentionally selected collection of published theoretical papers, systematic and scoping reviews, empirical educational studies, and institutional guidance cited in this article. The source base includes directly cited contributions relevant to theoretical foundations, human-AI regulation, instructional trials, and ethical governance. Sources are interpreted according to their evidentiary role: foundational theory defines constructs; reviews describe research landscapes; primary studies offer context-bounded evidence; policy documents indicate institutional safeguards. The corpus is illustrative and purposive, not a statistically representative sample [6], [26], [27].

Relevance for inclusion in the argument was judged conceptually: a source needed to clarify at least one of the four RQs by defining a central construct, characterizing an educational AI function, reporting directly relevant learning activity or outcome, identifying a counterargument, or setting out governance responsibilities. Sources on non-generative AI were not treated as demonstrations of GenAI effects. Theory sources predating the current generation of AI tools were retained when needed to interpret motivation, metacognition, scaffolding, or pedagogical agency [24], [25], [28]. A source's appearance in the bibliography does not indicate that it was selected by a previously documented exhaustive eligibility process.

This conceptual review did not undertake or document a reproducible, date-stamped, database-specific search, a screening log, independent dual review, a standardized risk-of-bias appraisal, or a record-level extraction dataset. None is retrospectively asserted here. This limits claims about coverage, prevalence, comparative strength of evidence, and publication bias. Instead, the revised analysis makes the relevant source-to-proposition relationships visible and describes the reasoning used to derive its conceptual framework. It cannot be treated as a systematic literature review.

2.3. Comparative Analytical Procedure

The conceptual comparison is articulated in four transparent interpretive steps. First, publications were considered for propositions about instructional assistance, adaptive mechanisms, self-regulation, and institutional responsibility. Second, propositions were compared along common distinctions: assistance versus independent outcomes; general responsiveness versus diagnostic adaptation; and learner control versus technological substitution. Third, apparently conflicting or context-dependent claims were examined to identify plausible moderators, including task demands, prior expertise, assessment setting, and the amount or timing of AI support. Fourth, the resulting distinctions were organized as design propositions in Sections 3.1 and 3.2. The procedure is an explicit account of interpretive comparison, not a claim of blinded coding, consensus scoring, or a newly collected participant dataset [8], [17], [20].

A proposition was treated as a technology affordance only when it described what the system can provide; as an educational process when it concerned how a learner or educator engages with assistance; and as an outcome only where a cited study actually measured an outcome. Contrasts were retained where the studies differed in population, intervention structure, or measurement. The analysis thus avoids treating a conceptual article, a review-level trend, and a randomized experiment as equivalent forms of evidence. Specific examples are reported in Table 3.2 without presenting them as results of an exhaustive search.

2.4. Conceptual Definitions and Evidence Limits

GenAI denotes models capable of producing context-responsive linguistic or other instructional content; personalization denotes tailoring that content or pathway to a stated or inferred learner characteristic. Educational adaptation additionally implies an evidence-informed adjustment of support as learning progresses. Learner agency refers to meaningful influence over goals, interpretation, and choices, whereas self-regulated learning (SRL) denotes goal-directed planning, monitoring, and reflection. Autonomy as a psychological need in self-determination theory is not identical to observable independence from a tool. These construct boundaries draw on personalization scholarship and established motivational and SRL theories [11], [23], [24], [25].

The paper contains no new interview, questionnaire, participant sample, machine-learning model, coded trial database, or inferential statistical analysis. It therefore reports no invented effect sizes, confidence intervals, quality ratings, inter-rater reliability, or causal estimates. The claims made from primary empirical publications remain bounded by the designs and educational contexts of those publications. The proposed agency-preserving loop is a conceptual output that requires future falsification, comparative evaluation, and validation.

2.5. Proposition Development and Human-Centred Framework

The synthesis contrasts three possibilities rather than assuming one educational effect. First, AI support may lower unnecessary barriers to learning; second, the same support may permit learners to bypass the reasoning they need to develop; and third, structured, contingent support may maintain productive challenge while preserving choice. The comparison asks what educational evidence is needed to distinguish these possibilities, how responsibility is allocated, and which outcomes must be independently observed. The resulting conditional propositions are organized by the four RQs in Table 3.3.

The initial framework integrates: (a) diagnostic fit between evidence of learning and the form of assistance; (b) graduated support calibrated to task and expertise; (c) meaningful learner decision rights; (d) verification and reflective explanation; (e) independent transfer checks; and (f) educator accountability, privacy, and equity. These elements elaborate earlier hybrid human-AI, personalization, agency, and self-regulation perspectives by specifying the conditions under which adaptive assistance could be considered agency-preserving [11], [14], [15], [29]. They are linked as a design decision sequence, not six experimentally established variables.

The proposed distinction between assisted achievement and unassisted transfer is central. Increased performance during tool use is not itself evidence of stronger autonomy; a plausible positive interpretation requires independent goal setting, monitoring, explanation, and performance after assistance is withheld. Conversely, short-term dependence may be instructionally justified during novice learning if carefully designed scaffolding is subsequently faded. These are conditional hypotheses and should be tested within defined tasks and populations rather than generalized from the present review.

Evidence-to-proposition traceability is provided through the source contrasts in Table 3.2, the bounded answers in Table 3.3, and the mechanism-and-indicator matrix in Table 3.5. Source identities and reference numbers are linked to the accompanying claims, and the relevant inferential limits are acknowledged. The analysis does not report systematic study counts, formal source-quality scores, pooled effects, or experimental validation of the framework.

3. Results and Discussion

3.1. Results of the Conceptual Analysis

3.1.1. Comparison with Existing Conceptual Perspectives

The literature provides overlapping but non-identical explanations of how educational AI may relate to human decision-making. Hybrid human-AI learning technologies foreground the allocation of regulatory responsibility; work on multiple personalization pathways addresses how educational resources might be differentiated; pedagogical-agency frameworks emphasize human judgement and ethical participation; and the present analysis adds a proposed decision sequence connecting diagnostic adjustment to learner choice and unassisted transfer [11], [14], [15]. The distinction is one of proposed explanatory focus, not proof that existing frameworks omit autonomy or that the present framework is empirically superior.

Table 2. Prior Perspectives Compared with the Proposed Agency-Preserving Loop

Perspective and source	Central insight and the remaining conceptual question
Hybrid human-AI learning; Molenaar [14]	Human and algorithmic responsibilities must be combined; independent-transfer criteria are not the sole organizing emphasis.
Complementary personalization; Brod [11]	Different approaches to personalized learning may be combined; personalized response is not itself learner autonomy.
Human-AI pedagogical agency; Haro-Sarango [15]	Cognition, ethics, and agency are explicitly interconnected; the present proposal adds a conditional classroom decision sequence.
Present agency-preserving loop	Checks diagnostic fit, learner choice, feedback verification, and independent transfer; this proposed loop remains untested.

Source: Comparative conceptual interpretation of the cited frameworks; the proposed model is an author-derived, untested extension.

Table 2 narrows the claimed novelty. Molenaar's hybrid model already makes human involvement integral to learning technologies, while Brod argues that personalization can follow multiple complementary routes. Haro-Sarango explicitly frames cognition and ethics in terms of human-AI agency [11], [14], [15]. Accordingly, the proposed contribution is not the generic assertion that humans should remain in control. It is the more discriminating criterion that an AI-supported adaptation should be appraised in two separate stages: whether support responds to a demonstrated instructional need, and whether it preserves opportunity for learner judgement and later independent execution.

This formulation has clear limits. It does not presume that all tasks benefit from removal of assistance or that one learning pathway suits all learners. It allows a teacher to determine when complete explanations are justified, when prompts or hints should replace solutions, and when independent work is an appropriate assessment of transfer. The resulting criterion may be particularly useful where the convenience of immediate AI output risks obscuring the acquisition of durable competence, a concern raised in literature on cognitive offloading and self-regulation [16], [19], [30].

3.1.2. Contrasting Source-Level Educational Propositions

Table 3 illustrates why the consequences of GenAI cannot be collapsed into an overall benefit-or-harm judgment. Evidence differs in educational level, type of AI assistance, comparison condition, and measured outcome. Studies of mathematics practice, problem solving, peer assessment, and self-regulation provide different windows onto performance and learner processes [8], [9], [17], [20]. These comparisons are selected illustrations of inferential differences; they are not a statistical summary or exhaustive enumeration of the literature.

Table 3. Source-Anchored Contrasts Relevant to Autonomy-Preserving Assistance

Evidence contrast	Published research context	Bounded interpretive implication
AI-assisted practice vs independent learning	High-school mathematics intervention [8]	Distinguish performance with AI from subsequent unassisted achievement; no generalization to

Evidence contrast	Published research context	Bounded interpretive implication every subject.
Performance depends on task and design	University creative problem-solving study [9]; experimental synthesis [10]	Task outcomes and assessment conditions differ; do not infer universal autonomy gains or losses.
Structured assistance vs unrestricted output	GenAI peer-assessment trial [20]; mathematical scaffolding [21]	Instructional structure can matter; compare guidance, student decisions, and opportunities to explain.
Motivation and self-regulation vs transfer	School randomized trial [17]; learner-questioning study [18]	Regulation, subjective support, and durable independence are distinct outcomes requiring different measures.

Source: Critical interpretation of cited primary studies and reviews; the final column contains the authors' bounded conceptual inference rather than a reported pooled finding.

One contrast is between performance obtained during access to an AI tutor and the durable competence demonstrated without the tool. Bastani and colleagues investigated performance with AI assistance and subsequent learning, showing why immediate gains are an incomplete indicator of educational value [8]. Urban and colleagues studied creative problem-solving performance under a different experimental context [9]. Taken together, these reports support the need to specify the outcome and assessment condition before drawing conclusions about autonomy; they do not prove a single cross-context causal pathway.

A second contrast concerns the structure of assistance. Research on GenAI-based peer assessment and mathematically scaffolded problem solving examines deliberately organized learning interactions, while work on learner questioning and perceived self-regulation draws attention to regulation during use [18], [19], [20], [21]. Reviews of feedback systems and critical thinking describe additional design considerations, but a review of prior studies should not be conflated with a new controlled estimate of independent skill transfer [30], [31], [32]. A plausible interpretation is that the amount and purpose of AI support, and the requirement to explain or verify its output, are better discriminators than the mere presence of the tool.

3.1.3. Integrated Propositions and Limits of Inference

The four research questions yield four provisional conceptual propositions. RQ1 distinguishes generic responses from evidence-responsive adaptation; RQ2 proposes that scaffolding supports agency when it leaves the learner responsible for goals, reasoning, verification, and later independent transfer; RQ3 positions privacy, equity, task requirements, and teacher accountability as constraints on this relation; and RQ4 translates these distinctions into a conditional design sequence and a future measurement agenda. Table 4 links each question to its stated inferential boundary.

Table 4. Research Questions, Bounded Conceptual Propositions, and Evidence Limits

Research question	Bounded conceptual proposition	Relevant source / unresolved question
RQ1: What constitutes adaptation?	An AI reply is not adaptive unless learning evidence informs an instructional adjustment.	Personalization and hybrid-AI perspectives [11], [14]; criteria require application testing.
RQ2: How is learner agency affected?	Scaffolding may support autonomy when learners retain choices, reasoning, and independent practice.	SRL, SDT and scaffolding [24], [25], [28]; no causal effect demonstrated here.
RQ3: What constrains these pathways?	Learning context, task demands, fairness, and professional oversight constrain responsible design.	Educational guidance and contextual research [27], [33]; trade-offs vary by setting.
RQ4: What should be evaluated?	Compare diagnostic fit, help fading, choice, verification, and no-AI transfer.	Experimental educational work [8], [17]; complete loop remains unvalidated.
Cross-cutting uncertainty	Assistance is not intrinsically beneficial or harmful; effects may depend on prior knowledge and task.	Adjacent cognitive-offloading work [16], [19]; stronger direct tests are needed.

Source: Authors' integrative conceptual synthesis of the sources discussed; proposed relationships are not validated intervention effects.

The central proposition can be stated as a conditional design claim: GenAI support should be regarded as potentially agency-preserving when it is tied to identifiable learning needs, permits meaningful learner choice and contestation, and is accompanied by opportunities to demonstrate understanding independently. This formulation joins process-level monitoring and learner decision-making without equating either with a measured outcome. It is consistent with theoretical distinctions among motivational autonomy, self-regulation and scaffolding, although its complete sequence is an author-derived model [23], [24], [25], [28].

Tables 2-4 therefore report three different analytical outputs: comparison with existing frameworks, contrasts across identifiable sources, and bounded propositions linked to the research questions. They do not establish prevalence of effects, the representativeness of the source base, or whether the proposed design conditions cause greater autonomy. Assessing those questions requires a separate preregistered or transparently documented systematic review and, for causal inference, suitably designed empirical evaluation.

3.2. Discussion

3.2.1. Personalization, Adaptation, and Instructional Contingency

A key implication of the conceptual analysis is that personalization should be treated as a pedagogical decision rather than a surface feature of generated text. A plausible adaptive loop begins with evidence of what the learner understands, determines an appropriate form of support, monitors the learner's response, and permits subsequent adjustment. The review literature documents diverse forms of AI-supported personalization, but its breadth also makes direct comparisons difficult when applications do not share the same diagnostic or instructional mechanism [12], [13], [34], [35]. A tool that merely restates an explanation in different words is not necessarily adapting to a verified learning need.

Constructivist perspectives are relevant because learner understanding depends on actively interpreting and applying explanations, not simply receiving them. Research and reviews on educational GenAI describe several settings in which generated feedback, examples, or prompts can support engagement; they do not establish that fluent answers automatically yield knowledge construction [1], [6], [7]. The present framework therefore treats explanation generation as a possible input to learning, whereas conceptual change and independent application remain separate educational outcomes. This separation avoids confusing the affordance of a technology with evidence of a learner's development.

Scaffolding provides a more specific lens for the design of support. Wood, Bruner, and Ross describe tutoring as contingent assistance directed towards problem solving, not simply the delivery of correct responses [28]. In AI-supported instruction, a useful analogy is to offer a hint, ask for an explanation, or prompt error checking before giving a complete solution. Yet human scaffolding involves judgement, context, and social responsibility that cannot be assumed to be reproduced by an AI model. Research on intelligent tutoring and digitally scaffolded SRL offers relevant adjacent perspectives, without being direct demonstrations of the same mechanism in generative systems [29], [36], [37].

The distinction also clarifies what an adaptive decision rule must contain: evidence about current understanding, a criterion for the level or format of help, and an opportunity to revise that help as competence develops. Brod's discussion of multiple personalization pathways and Molenaar's hybrid model suggest that educational adaptation should involve both technological flexibility and human pedagogical decisions [11], [14]. The proposed additional criterion is the explicit reassessment of

independent performance after meaningful help, rather than the assumption that a tailored response has already strengthened autonomy.

Recent syntheses demonstrate why the problem requires conceptual precision. Amofa and colleagues discuss opportunities and complications in higher education; Qian reviews the range of GenAI pedagogical applications; and Liang and colleagues examine human-AI interaction across educational research [5], [6], [26]. These reviews provide context, but the present manuscript does not treat their coverage, populations, or conclusions as interchangeable. Their role is to motivate differentiated instructional questions, not to validate the proposed loop by citation alone.

Task complexity creates an important countercase. When a learner has insufficient prerequisite knowledge, detailed explanations may be necessary rather than detrimental, and an immediate demand for independent performance may simply expose the learner to avoidable failure. Conversely, unrestricted access to finished solutions can weaken opportunities to practice complex reasoning when competence is the intended objective. The distinction should therefore be evaluated relative to a specific learning goal and a planned progression in support, not by imposing a universal limit on AI use. Experimental results obtained in different learning tasks are consistent with the need for such context-dependent analysis [8], [9], [21].

An illustrative instructional sequence would ask students to attempt a task, explain their current reasoning, request an AI hint if needed, inspect the evidence and limitations of the response, and attempt a parallel problem without AI. The educator would adjust assistance in light of the learner's demonstration of understanding and disclose when AI use is appropriate. These steps are design recommendations derived from the conceptual synthesis; they are not reported observations from a new classroom experiment.

The first substantive proposition is thus conditional: personalized AI support is more plausibly autonomy-preserving when adjustment is justified by learner evidence and when the instructional sequence maintains opportunities for independent explanation and transfer. The claim is not that these conditions have already been shown to increase achievement in every context. Rather, they define what would need to be observed in future comparisons of adaptive learning designs.

3.2.2. Autonomy, Agency, and Self-Regulated Learning

Learner autonomy, agency, and self-regulated learning should not be collapsed into a single outcome. Agency denotes the learner's capacity to influence goals and decisions within an activity. SRL concerns the processes of planning, monitoring, adjusting strategies, and reflecting on performance. In self-determination theory, autonomy refers to experiencing action as volitional, alongside the needs for competence and relatedness; this is not equivalent to never requesting help [23], [24], [25]. GenAI may support one construct while leaving another unchanged or even constraining it, so all three need separate interpretation.

Self-determination theory offers one explanatory perspective: assistance may be motivating when it supports a learner's sense of choice and competence, but controlling or opaque recommendations may undermine perceived volition [24]. Recent reviews inspired by the theory, including Balayar's review of AI-supported learning, extend the conversation to contemporary educational technology while not replacing the foundational meaning of its constructs [38]. A learner can legitimately choose to use support; the methodological question is whether that use preserves ownership of goals and choices rather than merely increasing satisfaction with a tool.

The relation between agency and cognitive offloading is similarly conditional. Offloading can conserve effort for more demanding tasks, yet it can also bypass practice that is necessary to acquire a skill. A scoping review explicitly addresses this tension in higher education, while research on perceived SRL and cognitive offloading raises related, but differently measured, questions [16], [19].

The present article therefore does not categorize all offloading as harmful. It proposes testing whether the functions delegated to AI are peripheral to, or constitutive of, the learning objective.

Zimmerman's overview of SRL and Panadero's comparison of SRL models provide a defensible theoretical basis for distinguishing forethought, performance regulation, and self-reflection [23], [25]. At forethought, the learner chooses goals and strategies; during performance, the learner monitors understanding and seeks help; and during reflection, the learner judges what has been learned and what still requires practice. Research on multimodal and AI-supported regulation shows why traces of strategy use may be informative, while such traces must not be confused with autonomy outcomes themselves [29], [36], [37].

Table 5 translates these theoretical phases into conditional GenAI assistance and observable learner responsibilities. The final row is explicitly an author-proposed adaptation check after reflection, not an additional phase attributed to Zimmerman's original model. Its purpose is to make decisions about whether help should be reduced, modified, or maintained, based on evidence from a subsequent task.

Empirical findings should be interpreted at the level they measure. Fütterer and colleagues' randomized investigation of GenAI support considers school students' regulation and related outcomes, whereas studies of questioning behaviour or perceived regulation may observe particular interactions or self-reports rather than durable independent competence [17], [18], [19]. The educational question is not settled by showing that students ask more questions, feel more supported, or finish a task faster. A stronger validation would include independent reasoning, transfer to a comparable task, and the ability to evaluate AI suggestions critically.

Reviews on critical thinking and SRL identify areas of concern across educational settings, but they do not justify assigning one effect to every task or learner [30], [39], [40]. The following table is consequently offered as a set of instructional propositions. It should be evaluated against authentic learner behaviour and curricular objectives before being presented as a validated pedagogical intervention.

Table 5. Self-Regulated Learning and Graduated GenAI Assistance

SRL stage	Potential GenAI role	Learner responsibility	Proposed observation or design check
Forethought	Suggest goals, resources or alternative plans.	Choose goals, explain priorities, select strategies.	Can the learner justify the plan without copying an AI suggestion?
Performance	Offer hints, examples and focused feedback.	Attempt task, monitor progress, verify guidance.	Record the level of help and independently explain key steps.
Self-reflection	Prompt error analysis and alternative explanations.	Evaluate mistakes and identify remaining gaps.	Explain in one's own words what was learned and what remains uncertain.
Adaptation check (proposed)	Suggest reduced or revised support for a next task.	Decide whether to adopt help and attempt transfer.	Compare performance on a relevant task without the prior level of AI support.

Source: Authors' conceptual elaboration of Zimmerman and Panadero; the adaptation-check row is an explicitly proposed extension, not part of an established SRL phase sequence.

The revised table makes the distribution of responsibility explicit. AI can suggest a practice strategy, but the learner must select and justify a goal; AI can offer feedback, but the learner must investigate its grounds; AI can summarize an error, but the learner must explain how their understanding changed. Fading assistance is appropriate only where independent performance is a meaningful goal and the learner has a fair opportunity to demonstrate it.

Educators have a role more substantive than permitting or prohibiting AI tools. Their design choices determine whether students are asked to justify decisions, compare alternative explanations,

and disclose how generated content affected their work. Studies of structured peer assessment, scaffolding and feedback suggest useful contexts in which these design choices can be investigated [20], [21], [31]. These studies differ in setting and measurement, so their collective relevance is methodological rather than proof of a universal treatment effect.

Balance also involves potential differences in prior expertise, self-efficacy, and task pressure. Students with limited prior knowledge may need more guided practice, while more experienced learners may benefit from fewer hints and greater responsibility for selecting strategies. Research concerning motivation in foreign-language learning and engagement in vocational education illustrates why learner population and task context cannot simply be abstracted away [41], [42]. The proposed model treats these factors as moderators to be tested, not as established effects derived from the present literature sample.

The second substantive proposition is therefore that learner agency should be evaluated as a process and an outcome distinct from personalization. Relevant evidence would include control over learning goals, strategic help-seeking, the quality of source verification, an independently articulated explanation, and transfer to comparable work without GenAI. Student satisfaction and assisted completion may still be useful metrics, but neither is an adequate standalone proxy for autonomy.

3.2.3. Ethical Safeguards and Human Accountability

An autonomy-preserving adaptive loop is inseparable from governance. AI-supported instruction may involve the collection of learner prompts, performance traces, preferences, and feedback, while algorithmically produced recommendations can influence educational decisions. UNESCO's human-centred guidance emphasizes the need to consider agency, inclusion, data governance, and the responsibilities of educational institutions [27]. The proposed model therefore treats oversight as a condition of legitimate adaptation, not as a decorative ethics statement added after the technology is deployed.

Human-centred governance should not be conflated with a claim that AI can replace a teacher's relational or professional judgement. Human-AI pedagogy may create meaningful co-learning arrangements, but the educator still sets the learning objective, judges assessment appropriateness, and remains answerable for consequential decisions [14], [15], [43]. A student should be able to question a recommendation and obtain a comprehensible explanation of why an instructional route is being proposed. That right matters both pedagogically and ethically.

Source comparisons reveal a conceptual convergence and a residual gap. Existing human-AI perspectives discuss agency and responsibility; personalization literature discusses tailoring; and research on cognitive offloading emphasizes the consequences of delegating mental work [11], [15], [16]. The present framework links these strands through a specific educational test: can the learner verify, contest, and eventually perform the relevant intellectual operation without the same level of AI assistance? The test is normative and evaluative, not an empirically established mechanism.

Privacy constrains which adaptive signals can legitimately be collected. Institutions should specify what learner information is required, which data are transmitted to external providers, retention and access limits, and routes for seeking redress. The need for personalization does not by itself justify indefinite collection of performance or behavioural traces [7], [27]. The model consequently distinguishes a valid instructional use of learner evidence from excessive surveillance: educational benefit should be demonstrated in relation to the sensitivity and necessity of the data.

Transparency also involves epistemic reliability. GenAI output may be articulate while still unsupported or inaccurate, a concern repeatedly raised in educational GenAI scholarship [1], [2], [3]. Verification should be built into learning activities: students can compare generated statements with course readings, identify uncertainty, and explain which evidence warrants a decision. These practices

preserve opportunities for critical judgement, but their effectiveness needs to be measured rather than simply assumed from the presence of a checking instruction.

Equity requires more than nominal tool availability. Differences in internet access, digital literacy, language and disability accommodation can alter who benefits from AI-mediated instruction. Evidence on diverse educational applications and conceptual accounts of technology-enabled learning underscores the need to preserve alternative routes to participation [4], [41], [42]. Where monitoring or personalization relies on intensive data collection, equity and privacy obligations may also pull against each other. These trade-offs should be assessed in each institutional context rather than treated as automatically resolved by general policy commitments.

Accountability includes academic integrity and consequential assessment. The conditions under which students may use generated explanations, the requirement to disclose use, and methods for evaluating independent competence should be set by educators and institutions rather than delegated to tools. Scholarship on authentic assessment and AI-supported integrity issues helps identify why assessment design is a necessary part of responsible deployment [33]. A proposed agency-preserving system should permit teacher review, learner challenge, and correction of misleading guidance.

Table 6 expresses the framework as a sequence of design decisions with potential indicators. Each element addresses a different weakness identified in the comparisons above, and every indicator is proposed for future evaluation rather than claimed as a measured finding of this review.

Table 6. Agency-Preserving Adaptive-Learning Loop: Mechanisms and Testable Indicators

Design criterion	Proposed mechanism	Learner / educator decision	Potential indicator for future testing
Diagnostic fit	Learning evidence informs the form and intensity of support.	Educator checks needs; learner describes difficulty.	Justified match between observed need and selected feedback.
Graduated assistance	Hints or explanations change as competence develops.	Learner requests help; educator sets fading conditions.	Assistance intensity and change across equivalent tasks.
Learner choice	The learner retains control over goals and meaningful decisions.	Learner chooses and justifies strategies and tool use.	Recorded goal choices and reasoned decisions.
Verification and reflection	AI claims are questioned rather than accepted at face value.	Learner checks evidence, explains errors, and reflects.	Accuracy and quality of independent source verification.
Independent transfer	Learning is assessed apart from assisted completion.	Learner attempts analogous work without previous assistance.	Unassisted reasoning and transfer performance.
Accountable, equitable oversight	Data governance, access, and professional judgement constrain use.	Institution sets safeguards; educator reviews consequential decisions.	Privacy compliance, access equity, and appeal or correction pathways.

Source: Authors' proposed conditional framework, informed by hybrid human-AI education, personalization, scaffolding, SDT, SRL, and ethical guidance [11], [14], [24], [25], [27], [28]. No component has been validated as part of this complete model.

Table 6 makes the proposed contribution operationally distinguishable from a catalogue of ethical principles. Diagnostic fit specifies why assistance is offered; graduated help specifies how it changes; learner choice and reflective verification specify what cannot be delegated without undermining agency; independent transfer specifies what a future evaluation should observe; and institutional accountability constrains how evidence is used. A failure at any stage should prompt reconsideration of the design rather than an automatic declaration that the technology is autonomy-enhancing.

The framework should be interpreted in dialogue with, not as a replacement for, earlier models. Molenaar's hybrid human-AI perspective already acknowledges human regulation, Brod develops

complementary paths to personalization, and Haro-Sarango considers pedagogical agency in a human-AI framework [11], [14], [15]. The narrower conceptual advance argued here is the explicit addition of an independent-transfer and contestability criterion to an evidence-responsive support loop. Whether this criterion improves student learning outcomes remains a hypothesis that must be tested under comparable instructional conditions.

There are also credible counterexamples. Intensive assistance may be appropriate for novice learners when immediate independent task completion would be unrealistic; permanent tool access may itself be an authentic condition of professional work; and a learner's subjective sense of autonomy may not track objective performance without help [9], [17], [24]. The framework consequently does not require minimizing AI in every activity. It requires matching support to the curricular target and deciding explicitly when unassisted transfer is a relevant success criterion.

For educators, the practical implication is to design tasks with an intentional escalation or fading rule, encourage explanation and verification, and determine whether independent performance is part of the assessed competency. For institutions, it is to specify data permissions, accessibility, disclosure requirements and decision accountability. Research on feedback, multimodal tutoring and authentic assessment offers potential settings in which these decisions may be studied, without guaranteeing uniform outcomes across technologies and learners [31], [33], [44].

Future evaluation can compare unrestricted answer access, graduated hint-based assistance, and non-AI instructional support while keeping learning goals and assessment conditions comparable. Potential outcomes include goal-setting quality, use of self-explanation, source verification, help-seeking patterns, transfer performance without AI, and sustained SRL across time. Qualitative observation can investigate agency and perceived control alongside these measures. The findings of existing experimental and observational work justify such questions but do not substitute for a test of the proposed sequence [8], [10], [17], [45].

The analysis is limited by its purposive and non-exhaustive documentary basis, reliance on heterogeneous source types, lack of formal study-quality appraisal, and interpretive rather than coded or experimental derivation. It cannot establish effect prevalence, comparative efficacy or causality. The contribution is instead a clearly bounded design proposition: adaptive GenAI assistance deserves evaluation against both the quality of its pedagogical fit and the learner's continuing capacity to choose, verify and demonstrate competence independently, under accountable and equitable governance.

4. Conclusion

This conceptual review distinguishes three objects that educational GenAI discussions sometimes collapse: an AI system's capacity to respond, the instructional adaptation of support to demonstrated learning needs, and a learner's development of agency and self-regulation. Comparison with prior hybrid human-AI, personalization, and pedagogical-agency perspectives indicates that autonomy-centred design is not a novel theme in itself. The proposed contribution is more specific: an agency-preserving adaptive-learning loop linking diagnostic fit, graduated support, learner choice, verification, independent transfer and accountable governance. This sequence offers conditional propositions through which the four guiding questions may be considered; it does not demonstrate that the proposed sequence causes improved learning.

The pedagogical implication is to assess assisted performance and independent understanding separately, specify which cognitive work students should retain, and calibrate AI support to tasks and learner expertise. Privacy, equity and educator responsibility qualify those decisions. The review's non-exhaustive source base, heterogeneous evidence and lack of empirical framework validation limit the strength and generalizability of its claims. Future research should compare well-defined assistance conditions, observe learner decision-making and information verification, and test transfer after sup-

port is reduced. The resulting evidence could determine whether, when, and for whom the proposed framework offers advantages over existing human-centred approaches.

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