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Reconceptualising Learner Autonomy in Generative AI-Supported Higher Education: A Technology-Mediated Framework

Lu Quoc Vinh* 

Can Tho University
 Can Tho City, Vietnam

Nguyen Ngoc Chi Lan 

Can Tho University of Medicine and Pharmacy
 Can Tho City, Vietnam

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Abstract. Generative artificial intelligence (generative AI) creates an autonomy paradox in higher education: It expands access to feedback, explanation and learning support while also enabling learners to outsource parts of planning, reasoning, production, verification and evaluation. Recently, studies have started to examine learner autonomy in environments supported by generative AI, but they remain conceptually fragmented regarding how learner responsibility should be organised across AI-mediated academic work. This conceptual study addresses this problem with a conceptual analysis and a bounded integrative literature review drawing on 46 sources, of which 43 formed the substantive analytical corpus that spans foundational autonomy theory, self-regulated learning, metacognition, learner agency, AI literacy, feedback, assessment, academic integrity and generative AI. The synthesis identifies three mechanisms of reconfiguration—cognitive redistribution, authorship ambiguity and regulatory intensification – and proposes technology-mediated learner autonomy as a learner-level responsibility structure comprising five operational dimensions: goal-setting autonomy, prompting agency, critical verification, metacognitive regulation and ethical accountability. Human judgement preservation functions as the normative core that links these dimensions and provides a criterion for distinguishing between accountable learner-directed use and uncritical or dependent AI use. The framework offers a theoretically traceable basis for future empirical validation and for designing assessment, feedback and institutional guidance that makes learner responsibility visible.

Keywords: Learner autonomy; generative AI; human judgement; self-regulated learning; higher education

*Corresponding author: Lu Quoc Vinh; lqvinh@ctu.edu.vn

1. Introduction

Generative artificial intelligence (generative AI) is increasingly embedded in higher education. Students use generative systems for the following functions:

- to search for information;
- to organise ideas;
- to draft and revise texts;
- to obtain feedback;
- to translate or summarise material; and
- to evaluate aspects of their work.

These systems participate directly in intellectual activities that were traditionally performed by learners. Research must, therefore, examine not only whether students use generative AI but also how AI use changes the conditions under which learning, authorship, responsibility and academic judgement take place (Farrelly & Baker, 2023; Lim et al., 2023; Lo, 2023). These changes are particularly consequential for learner autonomy. Established accounts emphasise responsibility for:

- learning;
- goal setting;
- strategy selection;
- monitoring;
- reflection; and
- informed decision-making.

Generative AI can support these processes by providing immediate explanations, feedback, personalised assistance and iterative interaction, and it can also assume parts of planning, reasoning, drafting, evaluation and decision-making. This facility produces an autonomy paradox: Technological support may expand opportunities for self-directed learning while also enabling over-reliance and displacement of learner reasoning (Kasneci et al., 2023; F. Wang et al., 2025; Yan et al., 2024).

Recent research examines this relationship more directly. Essel et al. (2026) investigated undergraduate students' perceptions of generative AI and perceived learning autonomy in Ghana. Hamamra et al. (2026) found that, in ChatGPT-supported English as a Foreign Language (EFL) writing at a Palestinian university, the pedagogical value of AI support depended on students' AI literacy and ethical awareness, while students' technological confidence did not necessarily translate into evaluative competence or responsible AI use. Similar studies address reliance and resistance (F. Wang et al., 2025), metacognitive support (Xu et al., 2025), and learner agency (Yang et al., 2024). This evidence changes the problem formulation. The question is no longer whether generative AI affects learner autonomy, but what autonomy should mean when an external system participates in the intellectual work through which autonomy has traditionally been demonstrated.

1.1 Research Problem and Conceptual Gap

Established theories of learner autonomy remain indispensable for understanding responsibility, control, reflection, agency and self-direction, even though they were developed before learners routinely interacted with systems capable of generating substantive academic content containing arguments, explanations, feedback and evaluations. Generative AI, therefore, introduces a technological condition under which central autonomy concepts require reinterpretation rather than abandonment. Four conceptual difficulties are particularly important.

First, learner control becomes more difficult to infer when intellectual work can be distributed between learner and system. Second, successful task completion can no longer be assumed to demonstrate autonomous reasoning because a polished product may conceal substantial external generation or cognitive substitution. Third, reflection and monitoring must extend beyond learners' own cognition to include evaluation of the accuracy, appropriateness, limitations and role of AI-generated support. Fourth, responsibility increasingly encompasses questions of authorship, disclosure, acceptable assistance and accountability for decisions represented in academic work supported by AI (Cotton et al., 2024; Holmes & Miao, 2023; Moorhouse et al., 2023; Perkins, 2023).

Recent studies illuminate different parts of this problem: perceived learning autonomy (Essel et al., 2026), mediated autonomy in EFL writing (Hamamra et al., 2026), reliance and resistance (F. Wang et al., 2025), metacognitive support (Xu et al., 2025), and learner agency (Yang et al., 2024). Together, they clarify key mechanisms without integrating goal direction, AI interaction, verification, metacognitive control, ethical responsibility, authorship and final judgement within one learner-level account. Accordingly, the gap identified in the bounded corpus is not an absence of research on generative AI and learner autonomy but an integration and construct-definition gap. No single framework in the reviewed literature reorganised the dispersed responsibilities around which learners must continue to control, evaluate and remain accountable for the academic work generative AI participated in.

Self-regulated learning explains planning and monitoring; AI literacy supports informed AI interaction; feedback literacy explains critical engagement with feedback; and academic integrity establishes ethical boundaries – none alone specifies the overall responsibility structure required when cognitive and productive activity is shared with a generative system. This paper, therefore, conceptualises technology-mediated learner autonomy as a learner-level responsibility structure for regulating AI-supported learning. The construct is organised around five operational dimensions: goal-setting autonomy, prompting agency, critical verification, metacognitive regulation and ethical accountability.

These dimensions are governed by human judgement preservation as a normative guiding principle, rather than treating human judgement as a sixth equivalent dimension. The principle requires that learners remain ultimately responsible for evaluating technological assistance and for the academic decisions embodied in

their work. The theoretical contribution of this study lies not in claiming that generative AI affects learner autonomy, but in reorganising insights from neighbouring constructs regarding the way learner responsibility is preserved when cognitive work is technologically mediated. The five dimensions specify responsibility for learning purposes, regulation of AI assistance, epistemic verification, monitoring of understanding and dependence, and ethical authorship; human judgement preservation provides the normative criterion connecting them.

1.2 Aim, Objectives, and Research Questions

The aim of this study is to reconceptualise learner autonomy for generative AI-supported higher education by identifying how technological mediation changes the conditions under which autonomy is exercised, demonstrated and evaluated. The study has three objectives:

- To identify assumptions in established autonomy accounts that require reinterpretation;
- To analyse how generative AI redistributes cognitive work, responsibility, agency and judgement; and
- To synthesise a differentiated framework specifying learner responsibilities for technology-mediated autonomy.

These objectives are addressed through the following research questions:

RQ1: When learning in higher education is mediated by generative AI, which assumptions underlying established accounts of learner autonomy require reinterpretation?

RQ2: How does generative AI redistribute cognitive work, responsibility, agency and judgement in autonomous learning practices in higher education?

RQ3: What operational dimensions and normative conditions are required to conceptualise technology-mediated learner autonomy in generative AI-supported higher education?

The study addresses these questions through conceptual analysis and a bounded integrative literature review. The following sections establish the theoretical foundations, explain the synthesis, present the framework, discuss implications and identify priorities for empirical validation.

2. Literature Review

This section establishes learner autonomy as the baseline construct, examines self-regulated learning and metacognition as enactment mechanisms, and then considers generative AI, AI literacy, integrity, feedback, assessment and human judgement as conditions that reshape autonomous academic work.

2.1 Learner Autonomy as Responsibility, Control, Reflection and Agency

Learner autonomy has traditionally concerned learners' capacity to assume responsibility for decisions about learning. Holec (1981) foregrounds responsibility for objectives, methods, resources, monitoring and evaluation; Little (1991) emphasises the reflective and relational character of autonomy; and Benson (2011) conceptualises learner control across multiple dimensions of the

learning process. Together, these perspectives show that autonomy is not equivalent to learning alone or without assistance but concerns meaningful responsibility and control under particular social and pedagogical conditions.

For the purposes of this conceptual analysis, responsibility, control, reflection and agency are treated as interconnected organising principles rather than independent measurement dimensions. Responsibility concerns answerability for learning decisions; control concerns influence over purposes, processes, resources and evaluation; reflection concerns examination of understanding and strategy and agency concerns intentional choice and action (Bandura, 2001; Deci & Ryan, 2000). These principles support a relational conception of autonomy: Learners act through teachers, peers, tasks, feedback, resources, institutions and technologies. Sociomaterial perspectives, similarly, caution against treating learning as detached from the material and technological arrangements through which activity occurs (Gourlay, 2021; Psaros, 2022). Generative AI is, therefore, significant because it can participate in both the process and product of academic activity.

2.2 Self-Regulated Learning, Metacognition and the Enactment of Autonomy

Self-regulated learning helps explain how learner autonomy is enacted. Pintrich (2000) and Zimmerman (2000) describe processes such as goal setting, strategic action, monitoring, self-observation and evaluation. These processes overlap with autonomy but are not synonymous with it: Learner autonomy concerns broader responsibility and control over learning, whereas self-regulated learning explains cognitive, metacognitive, motivational and behavioural processes through which that responsibility can be operationalised.

Metacognition is particularly relevant to this distinction. Flavell (1979) conceptualised metacognitive monitoring as learners' awareness and regulation of their own cognitive processes. In generative AI-supported environments, however, monitoring must address not only what learners know and how effectively they are learning but also how external cognitive assistance is affecting their understanding and decision-making. Recent work on generative AI environments reinforces the importance of metacognitive support for self-regulated learning (Xu et al., 2025), while research on learner agency highlights differences between deeper and more superficial forms of engagement with generative AI (Yang et al., 2024).

This extension clarifies the boundaries of the framework. Metacognitive regulation concerns the learner's own comprehension, strategy effectiveness, uncertainty and dependence on external support. Critical verification, in turn, concerns the epistemic quality of AI-generated material, while prompting agency concerns how the learner regulates the type, depth and direction of cognitive assistance delegated to the generative system. These processes may co-occur, but their objects of regulation differ.

2.3 Generative AI, Cognitive Mediation and AI Literacy

Generative AI can provide explanations, examples, writing assistance, feedback, translation, summarisation and opportunities for dialogue (Kohnke et al., 2023;

Lo, 2023; Mhindu et al., 2026; Tlili et al., 2023). Across higher education and language education, reviews of generative AI use identify extensive pedagogical opportunities alongside concerns about reliability, over-reliance, critical thinking, assessment and responsible use (Qian, 2025; C. Wang et al., 2026; Yan et al., 2024). Consequently, the autonomy-related significance of generative AI cannot be determined simply by whether the technology is used.

AI literacy provides one part of the answer. AI literacy enables learners to understand the capabilities and limitations of AI, interact with systems purposefully, evaluate outputs, recognise potential risks and make informed decisions about use (Chan & Hu, 2023; Holmes & Miao, 2023; Yan et al., 2024). In this sense, AI literacy is a necessary enabling competence for technology-mediated autonomy. However, proficiency in using an AI system does not by itself establish autonomy. A learner may be highly skilled at eliciting sophisticated output while transferring substantial intellectual responsibility to the system.

This distinction makes the boundary between scaffolding and cognitive substitution central. AI assistance functions as a scaffold when it supports intellectual activity that remains meaningfully performed and evaluated by the learner. Examples include asking for alternative explanations, requesting feedback on a learner-generated draft, comparing possible approaches, or using AI to identify questions requiring further investigation. In contrast, cognitive substitution occurs when the system performs the intellectual operation that the task is intended to develop or assess and the learner cannot independently explain, evaluate, reconstruct or defend that operation.

Accordingly, the distinction should not be based on the amount of AI use alone. Four considerations are especially relevant: the intended learning outcome, the intellectual function delegated to AI, the learner's capacity to evaluate the resulting output, and the learner's capacity to account for the final decision or product. The same technological action may, therefore, constitute legitimate scaffolding in one task and inappropriate substitution in another. This task-dependent distinction is consistent with broader concerns about generative AI, assessment validity, and responsible educational use (Bearman & Ajjawi, 2023; Moorhouse et al., 2023; Perkins et al., 2024).

2.4 Academic Integrity, Authorship, Assessment and Human Judgement

Generative AI changes the relationship between academic process and product. AI-supported work may combine learner-generated and system-generated contributions, thereby complicating authorship, disclosure, originality, responsibility, and the validity of evidence used to infer learning (Cotton et al., 2024; Holmes & Miao, 2023; Perkins, 2023; Rudolph et al., 2023; Yu, 2023). These issues are not confined to one geographical region: recent African higher education research identifies challenges related to academic integrity that require transparent and context-sensitive responses (Guadu et al., 2025).

Feedback scholarship adds an epistemic dimension. Feedback becomes educationally useful when learners interpret, evaluate and act on it. Boud and

Molloy (2013) emphasise learner involvement in feedback processes, while Carless and Boud (2018) conceptualise feedback literacy as the capacity to appreciate, judge and use feedback. With AI-generated feedback, these responsibilities intensify because recommendations may be plausible without being reliable or disciplinarily appropriate. Autonomous learners, therefore, treat AI feedback as input for judgement rather than authoritative instruction.

Assessment clarifies the distinction between support and substitution further. If an assessment is intended to provide evidence of independent reasoning, transferring that reasoning to generative AI threatens the validity of the inference drawn from the submitted product. If the intended outcome includes critical use of technological resources, AI assistance may be legitimate if the learner can document, evaluate, and justify how it was used (Bearman & Ajjawi, 2023; Moorhouse et al., 2023; Perkins et al., 2024; Singh et al., 2026). Thus, the educational significance of AI use depends partly on the intellectual construct that the learning activity or assessment is intended to elicit.

These considerations explain why human judgement preservation is treated as a normative principle rather than another operational skill. Preservation does not require working without technological input; it requires that AI assistance does not acquire final epistemic or academic authority: Learners must remain able to accept, reject, revise or verify outputs and defend the reasoning represented in the final work.

2.5 From Learner Autonomy to Technology-Mediated Learner Autonomy

Throughout the emerging literature, three developments recur. First, autonomy is mediated through generative systems and broader sociomaterial relations (Gourlay, 2021; Hamamra et al., 2026; Psaros, 2022). Second, product quality cannot reliably provide evidence of autonomous reasoning when the distribution of intellectual work is hidden (Cotton et al., 2024; Moorhouse et al., 2023; F. Wang et al., 2025). Third, autonomy now includes responsibilities for verification, dependence monitoring, appropriate assistance, authorship, disclosure and final academic decision-making.

The resulting gap is, therefore, one of integration and construct definition. Research explains particular relationships and mechanisms, but the associated responsibilities remain distributed across neighbouring constructs and context-specific studies. Within the bounded corpus, no single framework can be organised around what must remain under meaningful learner control when generative AI participates in academic work. Table 1 positions the proposed construct in relation to adjacent concepts without treating those concepts as deficient.

Table 1: Positioning technology-mediated learner autonomy in relation to adjacent constructs

Construct and theoretical basis	Primary explanatory focus	Contribution to generative AI-supported learning	Responsibility not specified by the construct alone
Learner autonomy (Benson, 2011; Holec, 1981; Little, 1991)	Learner responsibility, control, reflection, and self-directed decision-making	Establishes ownership of learning goals and decisions	Does not explicitly specify how cognitive responsibility should be allocated when a generative system performs parts of planning, production, feedback or evaluation
Self-regulated learning/meta-cognition (Flavell, 1979; Pintrich, 2000; Xu et al., 2025; Zimmerman, 2000)	Planning, strategic use, monitoring, adaptation and evaluation	Explains how learners regulate cognition and learning processes, including the need to monitor AI dependence	Does not by itself determine authorship responsibility, ethical legitimacy of AI assistance or ownership of final academic judgement
AI literacy (Chan & Hu, 2023 ; Hamamra et al., 2026 ; Holmes & Miao, 2023 ; Yan et al., 2024)	Understanding, interacting with and critically evaluating AI systems	Enables purposeful use, awareness of limitations, risk recognition and output evaluation	Competent AI use does not necessarily establish who directs the learning process or remains responsible for the intellectual work
Learner/student agency (Bandura, 2001; Yang et al., 2024)	Intentional action, choice and influence over learning activity	Clarifies whether learners actively direct rather than passively follow AI-supported activity	Does not by itself specify verification, disclosure, authorship or the ethical boundaries of delegated cognitive work
Feedback literacy (Boud & Molloy, 2013; Carless & Boud, 2018)	Interpreting, evaluating and using feedback	Supports critical uptake rather than passive acceptance of AI-generated feedback	Focuses primarily on feedback processes rather than responsibility across goal setting, prompting, production, authorship and final judgement
Academic integrity (Cotton et al., 2024; Perkins, 2023)	Ethical conduct, transparency, authorship and acceptable academic practice	Establishes boundaries for legitimate AI use and disclosure	Specifies what use may be acceptable but does not fully explain how learners regulate AI support cognitively and metacognitively throughout learning

Construct and theoretical basis	Primary explanatory focus	Contribution to generative AI-supported learning	Responsibility not specified by the construct alone
Technology-mediated learner autonomy (proposed synthesis)	Accountable learner responsibility across AI-mediated academic work	Coordinates goal setting, regulation of AI assistance, verification, metacognitive monitoring, ethical accountability and final judgement	Does not replace adjacent constructs; specifies how their contributions are coordinated around continuing learner responsibility

Note. The distinctions are based on the conceptual synthesis of learner autonomy, self-regulated learning, AI literacy, feedback, academic integrity, assessment and generative AI literature reviewed in this study.

The integration mechanism is organised around five objects of learner responsibility: learning direction, regulation of technological assistance, epistemic evaluation, monitoring of understanding and dependence, and ethical authorship. The framework, therefore, coordinates, rather than replaces learner autonomy, self-regulated learning, AI literacy, feedback literacy and academic integrity. Human judgement preservation provides the normative link: AI may contribute to the process, but the learner remains able to evaluate that support, understand the work produced, and assume responsibility for final decisions.

3. Methodology

3.1 Conceptual Research Design and Rationale

This study employed a conceptual research design that combined conceptual analysis with a bounded integrative literature review. The design fits a construct-level problem rather than a prevalence estimate or intervention test: Does learner autonomy require clarification or reorganisation when generative AI participates in planning, production, feedback, verification and evaluation? Conceptual research is suited to clarifying and differentiating established constructs under changing theoretical or contextual conditions (Jaakkola, 2020).

The integrative review served a theory-building rather than exhaustive evidence-aggregation function, by enabling comparison of diverse literatures, identification of tensions, and theoretically informed synthesis (Snyder, 2019; Torraco, 2016). The review was bounded by disciplinary relevance, source type, publication period, conceptual contribution and analytical purpose and makes no claim to provide systematic or exhaustive coverage.

3.2 Review Boundaries and Search Strategy

The literature base was developed purposively and iteratively around the conceptual problem, with higher education and education research as the primary scope. Related work from education psychology, language education, assessment and educational technology was retained when it was related directly to autonomy, self-regulation, metacognition, agency, feedback, integrity, AI literacy, authorship, assessment or human judgement.

No lower publication-date limit was imposed on foundational theoretical literature because several constructs central to the analysis predate generative AI. Seminal works on metacognition, learner autonomy, self-regulated learning, motivation and agency were retained when they were necessary to establish the pre-AI conceptual baseline. For literature addressing generative AI directly, priority was given to publications from 2023 to 10 August 2026 – the period when publicly accessible generative systems became a major concern in higher education.

During revision, a documented supplementary search was conducted on 10 August 2026. ERIC served as the disciplinary education database and was supplemented by targeted retrieval, publisher and digital object identifier (DOI) verification, and backwards and forwards citation tracing for conceptually central sources. The search strengthened the currency and defensibility of the bounded corpus; it was not intended to convert the study into a systematic review. The supplementary search used five concept clusters.

- Cluster 1 was ('learner autonomy' OR 'learning autonomy') AND ('generative AI' OR 'generative artificial intelligence' OR ChatGPT) AND ('higher education' OR 'universit*');
- Cluster 2 was ('self-regulated learning' OR 'metacognit*') AND ('generative AI' OR ChatGPT) AND ('higher education' OR 'universit*');
- Cluster 3 was ('student agency' OR 'AI literacy' OR 'academic integrity' OR 'authorship' OR 'verification') AND ('generative AI' OR ChatGPT) AND ('higher education' OR 'universit*');
- Cluster 4 was ('sociomaterial*' OR 'posthuman*') AND ('digital' OR 'generative AI') AND ('learning' OR 'education');
- Cluster 5 was ('conceptual research' OR 'conceptual paper' OR 'integrative literature review') AND ('theory building' OR framework OR synthesis). Search expressions were adapted where necessary to the conventions of individual platforms.

The final reference list comprised 46 sources, of which 43 substantive sources formed the analytical corpus; Jaakkola (2020), Snyder (2019), and Torraco (2016) primarily informed research design and review procedures. The substantive sources were organised into five literature strands by principal analytical contribution. This classification was functional rather than mutually exclusive, because a source could inform more than one framework component.

3.3 Eligibility Criteria and Corpus Organisation

Sources were retained when they contributed directly to the conceptual problem. Inclusion required contribution to at least one of five purposes, namely:

- Establishing learner-autonomy foundations;
- Explaining regulatory, metacognitive, motivational or agentic processes;
- Identifying how generative AI mediates learning and redistributes cognitive work;
- Clarifying epistemic, ethical, authorship, feedback, assessment or integrity conditions; or
- Providing an adjacent theoretical perspective for construct differentiation.

Eligible material included peer-reviewed empirical studies, systematic or scoping reviews, conceptual and framework papers and theoretically influential books and chapters, and authoritative policy documents. Foundational sources were retained for theoretical significance; recent sources were prioritised for generative AI.

Sources were excluded when they focused primarily on model architecture, algorithmic performance, software engineering, commercial promotion or commentary without a substantive connection to learning, autonomy, responsibility, assessment, ethics or higher education. Technology-acceptance studies were retained only when they contributed directly to responsibility, agency, regulation, verification or accountability. Sources outside higher education was used only for foundational theory; duplicates and unverifiable records were excluded. Table 2 summarises the composition and analytical function of the bounded literature corpus.

Table 2: Structure and analytical functions of the bounded literature corpus

Primary literature strand	Inclusion focus	Analytical function	n
Foundational literature on learner autonomy	Theoretically influential work on learner responsibility, control, reflection, decision-making and autonomy	Establish the pre-generative-AI conceptual baseline and identify aspects of autonomy that require preservation or reinterpretation	3
Self-regulated learning, metacognition and agency	Literature addressing goal setting, strategic action, monitoring, reflection, motivation, metacognition and learner agency	Explain the regulatory and agentic mechanisms through which autonomous learning is enacted	7
Generative AI in higher education	Empirical, review and conceptual work on AI-supported learning, writing, feedback, reliance, learner support and agency	Identify how generative AI mediates learning practices, redistributes cognitive work and creates new autonomy-related demands	15
Academic integrity, feedback, assessment, and AI literacy	Literature on verification, feedback uptake, AI literacy, authorship, disclosure, ethical use, academic integrity and assessment	Clarify the epistemic and ethical conditions of responsible AI-supported academic work	11
Adjacent conceptual and theoretical perspectives	Conceptual work on AI-human relations, technology-mediated learning, assessment validity and sociomaterial perspectives	Test conceptual boundaries and distinguish technology-mediated learner autonomy from neighbouring constructs	7
Total substantive analytical corpus			43

Note. Three additional methodological sources – Jaakkola (2020), Snyder (2019) and Torraco (2016) – supported the research design and integrative review procedures rather than construct development.

3.4 Analytical Synthesis and Framework Construction

The analysis proceeded through five linked stages that were iterative rather than strictly linear; the developing framework was revisited as conceptual relationships and boundaries became clearer. First, baseline reconstruction identified established autonomy principles – responsibility, control, goal setting, reflection, monitoring, self-regulation and agency – that pre-dated generative AI. Second, analytical problematisation examined whether those assumptions required reinterpretation when generative AI participated in academic work, with a focus on cognitive redistribution, dependence, authorship ambiguity, verification, disclosure and responsible decision-making. Third, construct comparison examined what self-regulated learning, AI literacy, feedback literacy, academic integrity and assessment-oriented perspectives explain, and what remains outside their primary explanatory scope.

Fourth, cross-theoretical synthesis organised recurring learner-level responsibilities according to their primary object: learning purposes, interaction with AI, epistemic evaluation of outputs, monitoring of understanding and dependence and ethical authorship. Fifth, candidate components were retained only when they were conceptually distinct, specifically relevant to AI-mediated learning and explanatorily necessary. Overlapping concepts were merged and enabling competencies, contextual conditions and outcomes were kept outside the learner-level construct. Human judgement preservation was, therefore, retained as a normative core rather than a sixth operational dimension.

An analytical trace matrix linked literature strands and extracted conceptual contributions, reconfiguration mechanisms and framework elements. Table 3 summarises this trace. The dimensions were not mechanically extracted from individual studies; they emerged from recurring concepts and tensions across bodies of literature.

Table 3: Analytical trace from literature strands to framework components

Literature strand	Main conceptual contribution extracted	Framework element(s) informed	Representative sources
Learner autonomy	Responsibility for learning goals, decisions, reflection, monitoring and evaluation	Goal-setting autonomy, metacognitive regulation, underlying learner responsibility	Benson (2011); Holec (1981); Little (1991)
Self-regulated learning and agency	Goal setting, strategic action, monitoring, reflection, intentionality and learner agency	Goal-setting autonomy, prompting agency, metacognitive regulation	Bandura (2001); Deci and Ryan (2000); Pintrich (2000); Xu et al. (2025); Yang et al. (2024); Zimmerman (2000)

Literature strand	Main conceptual contribution extracted	Framework element(s) informed	Representative sources
Generative AI in higher education	AI-mediated production, learner–AI interaction, reliance, cognitive redistribution and increased verification demand	Prompting agency, critical verification, metacognitive regulation, human judgement preservation	Hamamra et al. (2026); Kasneci et al. (2023); F. Wang et al. (2025); Yan et al. (2024)
AI literacy and critical AI use	Understanding AI capabilities and limitations, purposeful interaction and critical evaluation of outputs	Prompting agency, critical verification	Chan and Hu (2023); Hamamra et al. (2026); Holmes and Miao (2023)
Feedback and evaluative judgement	Interpreting feedback, evaluating its quality and retaining responsibility for revision decisions	Critical verification, metacognitive regulation, human judgement preservation	Bearman and Ajjawi (2023); Boud and Molloy (2013); Carless and Boud (2018)
Academic integrity and authorship	Disclosure, ownership, acceptable use, transparency and responsibility for submitted work	Ethical accountability, human judgement preservation	Cotton et al. (2024); Guadu et al. (2025); Perkins (2023); Perkins et al. (2024)
Assessment validity	Alignment between AI assistance and the intellectual work that assessment is intended to elicit	Human judgement preservation, ethical accountability	Moorhouse et al. (2023); Perkins et al. (2024); Singh et al. (2026)
Sociomaterial and technology-mediated perspectives	Learning and agency are enacted through relations among learners, technologies, tasks and institutional conditions	Technology-mediated character of the overall construct	Gourlay (2021); Psaros (2022); Zawacki-Richter et al. (2019)

Note. Representative sources illustrate the analytical trace and do not imply a one-to-one derivation of framework elements from individual studies.

3.5 Analytical Robustness and Reflexivity

The robustness of the analysis was strengthened by examining both affordances and risks of generative AI rather than constructing a uniformly optimistic or pessimistic framework. Candidate dimensions were subjected to negative case and boundary checking, including cases where extensive AI use coexisted with

meaningful agency and cases where apparently independent completion concealed cognitive outsourcing (Cong-Lem et al., 2026; Hamamra et al., 2026; F. Wang et al., 2025; Xu et al., 2025).

A substitution test then asked whether autonomy would remain defensible if the relevant intellectual responsibility were transferred substantially to generative AI. The test distinguished assistance that supported learner reasoning, monitoring, verification and decision-making from assistance that replaced the central intellectual work a task is intended to develop or assess. Finally, the source-to-claim trace functioned as an audit trail that linked mechanisms and dimensions to specific literature strands. Because the study is conceptual rather than systematic, it did not use independent dual screening or statistical inter-rater procedures; this limitation is acknowledged in Section 5.6.

4. Conceptual Findings

The analysis generated two related findings. Three recurring mechanisms – cognitive redistribution, authorship ambiguity and regulatory intensification – reconfigure autonomy, while five distinct forms of learner responsibility respond under human judgement preservation as a normative core. Mechanisms and dimensions were retained only when they were conceptually distinct, relevant to generative AI-mediated learning and explanatorily useful; enabling competencies, contextual conditions and outcomes remained outside the construct.

4.1 Three Mechanisms of Reconfiguration

The three mechanisms represent different analytical loci rather than sequential stages: cognitive redistribution concerns how intellectual work is distributed between the learner and the generative system, authorship ambiguity concerns ownership and attribution, and regulatory intensification concerns additional decisions and controls introduced by AI participation. These three mechanisms may co-occur and are not an exhaustive taxonomy of the educational effects of generative AI.

4.1.1 Cognitive Redistribution

Cognitive redistribution occurs when functions previously performed predominantly by the learner, such as searching, explaining, generating alternatives, drafting, summarising, revising or evaluating, are partly transferred to a generative system. Such redistribution can provide scaffolding and immediate support, but over-reliance can reduce monitoring or outsource cognitive and metacognitive work (Kasneci et al., 2023; Qian, 2025; F. Wang et al., 2025; Yan et al., 2024).

The analysis distinguishes scaffolding from substitution by applying three criteria. First, the task–purpose criterion asks whether AI supports or performs the intellectual operation the task is intended to develop. Second, the explainability criterion asks whether the learner can reconstruct, explain and defend the reasoning represented in the output. Third, the decision–authority criterion asks whether the learner evaluated alternatives and retains the authority

to accept, modify or reject the generated contribution. AI assistance functions as scaffolding when these responsibilities remain substantially with the learner; it approaches substitution when the central intellectual operation and its evaluation are transferred to the system.

4.1.2 Authorship Ambiguity

Authorship ambiguity concerns the relationship between generated contribution and the learner's intellectual ownership of the submitted work. AI-supported academic products may develop through iterative combinations of prompts, generated outputs, human revision, external sources and final decisions. As AI contribution becomes more substantive, the visible product may no longer reveal which ideas, formulations, interpretations or judgements originated from the learner (Cotton et al., 2024; Perkins, 2023).

Authorship ambiguity is a condition of hybrid production, whereas ethical accountability is a learner response to that condition. The former concerns uncertainty over contribution and ownership; the latter concerns legitimate use, disclosure, non-misrepresentation and responsibility for the submitted work.

4.1.3 Regulatory Intensification

Regulatory intensification refers to additional decisions required, because learners regulate both their own learning and the scope and consequences of AI interaction. Beyond goal setting, strategy selection, monitoring and evaluation, learners must decide whether AI assistance is appropriate, what support to request and how to verify generated information. They must also monitor increasing reliance, interpret task permissions and decide how AI contributions should be represented (Chan, 2023; Holmes & Miao, 2023; F. Wang et al., 2025; Yan et al., 2024).

This interpretation is consistent with evidence that AI-supported learning involves reliance, evaluative competence and student agency rather than tool use alone (Hamamra et al., 2026; Yang et al., 2024). Table 4 clarifies the analytical object and learner-level consequences associated with each reconfiguration mechanism.

Table 4: Analytical distinction among the three mechanisms of reconfiguration

Mechanism	Primary analytical question	Autonomy-related problem	Illustrative learner responsibility
Cognitive redistribution	Where is the intellectual work being performed?	AI could support reasoning or replace the reasoning a task is intended to develop	Determine which intellectual functions may be delegated while retaining meaningful engagement with the target learning
Authorship ambiguity	Whose intellectual contribution does the resulting work represent?	Iterative human–AI production can obscure ownership and provenance	Distinguish learner and AI contributions and ensure that the final work can be explained and defended
Regulatory intensification	What additional decisions and monitoring arise because AI is involved?	Learners must regulate both their learning and their interaction with an external generative system	Control the level of assistance, verify outputs, monitor dependence and comply with relevant use requirements

Note. The mechanisms are analytically distinct but may co-occur within the same task. These three mechanisms are not intended as an exhaustive taxonomy of all educational effects of generative AI.

4.2 Defining Technology-Mediated Learner Autonomy

Technology-mediated learner autonomy is a learner-level responsibility structure through which learners retain accountable control over the purpose, scope, evaluation and intellectual ownership of AI-mediated academic work and remain responsible for the final academic judgement represented in that work. This definition retains the emphasis of autonomy on responsibility and control while recognising that responsibility and control are exercised through relations with generative systems, tasks, assessment conditions and institutions. Technology-mediated refers to the conditions of decision-making, not to technology becoming autonomous.

Three propositions define the boundary of the construct of technology-mediated learner autonomy. First, technology-mediated autonomy is not equivalent to independent task completion: Learners may legitimately use substantial external support while remaining autonomous. Second, it is not equivalent to AI competence: Technically sophisticated AI use does not demonstrate autonomy if the learner has surrendered substantive intellectual direction or evaluation. Third, it is not equivalent to academic compliance: Correct disclosure alone does not establish that the learner retained understanding, authorship or judgement. Technology-mediated autonomy is, therefore, a responsibility structure rather than a collection of AI-related skills. The five operational dimensions presented in Section 4.3 specify how that responsibility becomes observable.

4.3 Deriving the Operational Dimensions and Normative Core

The synthesis initially produced recurring concepts such as responsibility, goal setting, prompting, verification, monitoring, dependence, disclosure, authorship, integrity, accountability and judgement. Closely related regulatory concepts were merged; enabling competencies such as AI literacy and contextual conditions such as institutional policy were kept outside the construct; and concepts governing different loci of learner responsibility were retained separately.

4.3.1 Goal-Setting Autonomy

Goal-setting autonomy concerns responsibility for defining the learning purpose and the legitimate role and limits of AI support. It relates to what the learner is trying to accomplish and which parts of the task the learner should perform themselves.

4.3.2 Prompting Agency

Prompting agency concerns responsibility for regulating the type, depth and direction of cognitive assistance delegated to generative AI. It is not a prompt-writing skill: A technically effective prompt may still undermine autonomy if it transfers the target reasoning to the system (Yang et al., 2024).

4.3.3 Critical Verification

Critical verification concerns epistemic responsibility for treating generated outputs as provisional. It includes checking accuracy, source validity, disciplinary relevance, bias, completeness and consistency with independent evidence before deciding whether to accept, revise or reject an output.

4.3.4 Metacognitive Regulation

Metacognitive regulation concerns monitoring understanding, strategy effectiveness, uncertainty and dependence during AI-supported work. It relates to whether AI assistance is strengthening comprehension or merely producing fluent performance (F. Wang et al., 2025; Xu et al., 2025).

4.3.5 Ethical Accountability

Ethical accountability concerns the legitimacy and transparency of AI-supported work, including permitted use, accurate representation of AI contribution and authorship, non-misrepresentation, and responsibility for the final submission.

4.3.6 Human Judgement Preservation as the Normative Core

Human judgement preservation was not retained as a sixth operational dimension because it operates at a different conceptual level: The five dimensions specify forms of responsibility, whereas the normative core specifies whether those responsibilities remain genuinely learner directed. The principle of human judgement preservation is supported across work on mediated autonomy, AI literacy, learner agency, reliance and assessment validity, all of which distinguish technological capability from evaluative competence and attributable learner performance (Bearman & Ajjaw, 2023; Hamamra et al., 2026; F. Wang et al., 2025).

The normative core can be explained simply: AI could contribute to academic work, but the learner remains capable of evaluating evidence, revising or rejecting generated contributions, making the final academic decision and defending that judgement. Reasoned rejection or substantial revision can, therefore, provide stronger evidence of retained judgement than passive acceptance, because it shows that generated content remains contestable by the learner. Table 5 summarises the five operational dimensions, the normative core, and provides illustrative evidence through which learner responsibility may become visible.

Table 5: Structure and observable evidence of technology-mediated learner autonomy

Framework element	Distinctive responsibility	Boundary from adjacent elements	Illustrative observable evidence
Human judgement preservation – normative core	Retain authority for final interpretation and academic decision	Not an operational skill; evaluates whether the five dimensions remain genuinely learner-directed	Reasoned rejection or substantial revision of AI outputs; defence of final decisions; identification of limitations in accepted AI assistance
Goal-setting autonomy	Define learning purpose and legitimate scope of AI support	Concern's purpose and boundaries; not prompt execution	AI-use plan; stated learning goals; explicit boundaries on tasks to be retained by the learner
Prompting agency	Regulate what cognitive assistance is delegated during AI interaction	Concerns control of delegation, not technical prompt proficiency	Using prompts that request scaffolding rather than completed reasoning; deliberate prompt limitation; revision when assistance becomes excessive
Critical verification	Establish whether AI-generated claims or suggestions warrant acceptance	Concerns epistemic evaluation, not general monitoring of learning	Cross-checking sources; detecting fabricated or inaccurate claims; correcting bias; rejecting unsupported outputs

Framework element	Distinctive responsibility	Boundary from adjacent elements	Illustrative observable evidence
Metacognitive regulation	Monitor understanding, strategy, progress and dependence	Concerns the learner's own cognitive state and strategy rather than the truth of a particular AI claim	Identifying understanding gaps; changing strategy; recognising excessive dependence; independently reconstructing reasoning
Ethical accountability	Ensure that AI-supported work is legitimate, transparent, and responsibly attributable	Concerns ethical legitimacy and representation, not epistemic accuracy alone	Accurate disclosure; explanation of AI contribution; compliance with permitted-use boundaries; defensible authorship claims

Note. Observable evidence is illustrative rather than a validated measurement scale. The framework requires empirical validation before the indicators can be used as psychometric items or scoring criteria.

4.4 Proposed Conceptual Framework

The resulting framework represents technology-mediated learner autonomy as a normatively grounded responsibility structure rather than a linear sequence of AI-use skills. The framework distinguishes four analytical levels. Three mechanisms explain why autonomy is reconfigured, five operational dimensions specify how learner responsibility is enacted, and human judgement preservation states what must ultimately remain attributable to the learner. Educator scaffolding, assessment design, policy, feedback, disciplinary norms and access operate as enabling or constraining contextual conditions.

Figure 1 represents this layered structure. The figure separates mechanisms, operational dimensions, the normative core and contextual conditions so that they are not treated as interchangeable elements.

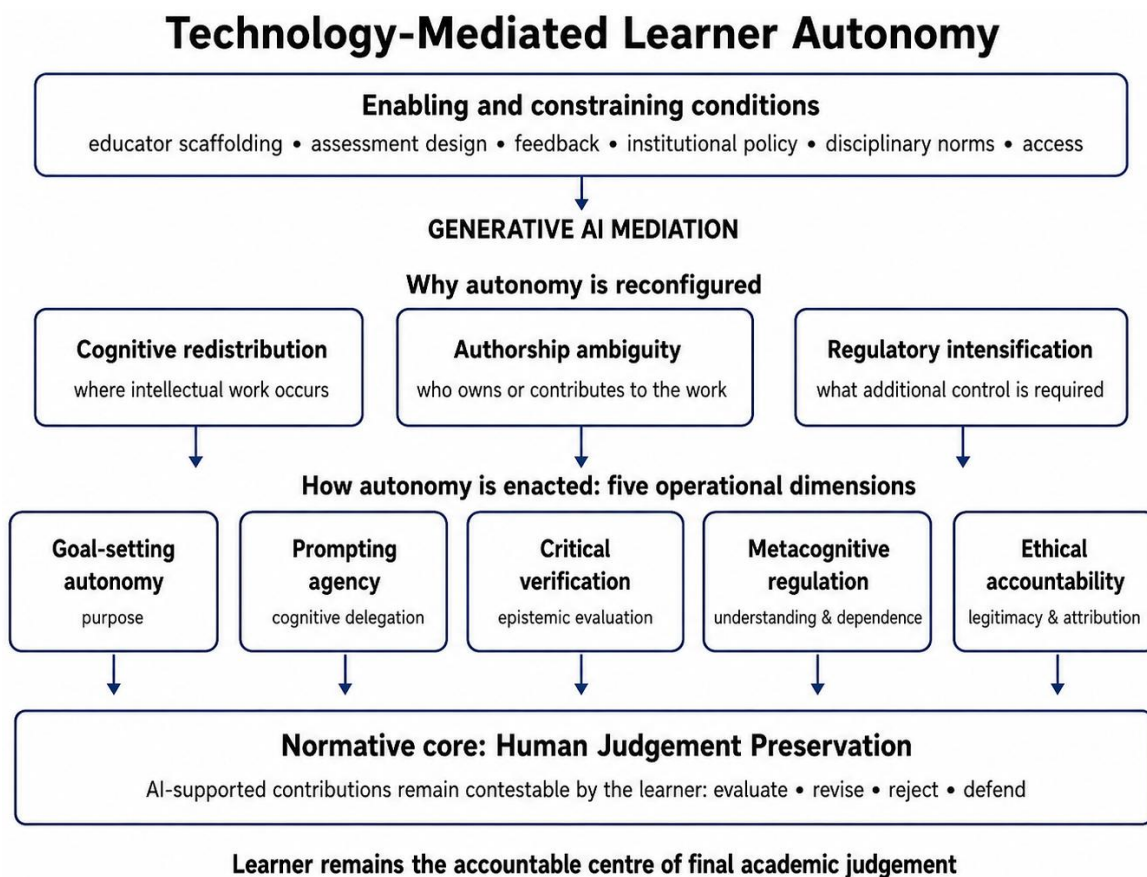


Figure 1: Layered conceptual framework of technology-mediated learner autonomy in higher education supported by generative AI

The framework does not suggest a fixed temporal sequence. All five dimensions can recur iteratively while learners redefine purposes, regulate assistance, verify outputs, monitor understanding and reconsider the legitimacy of AI use.

5. Discussion

The framework contributes to research on mediated autonomy, agency, AI literacy, reliance and self-regulation by specifying how learner responsibility is organised when generative AI participates in cognitive production, feedback, verification and academic decisions.

5.1 Positioning Technology-Mediated Learner Autonomy in Emerging Generative AI Research

Hamamra et al. (2026) suggest that mediated learner autonomy in ChatGPT-supported EFL writing depends on AI literacy, evaluative competence, ethical decision-making and contextual support, while Essel et al. (2026) examine the relationship between perceptions of generative AI and learning autonomy in Ghana. Rather than retesting these relationships, the framework of this study addresses a prior construct-level question: Which responsibilities should count as autonomous when AI participates in academic work?

Yang et al. (2024) foreground student agency, while Qian (2025) identifies autonomy, prompt literacy, over-reliance and cognitive or metacognitive outsourcing among emerging themes. The framework connects these concerns by distinguishing cognitive delegation, verification, dependence monitoring and ethical authorship.

The framework also differs from adjacent models regarding level of analysis. Institutional frameworks address governance (Chan, 2023), the Artificial Intelligence Assessment Scale addresses permissible AI involvement in assessment (Perkins et al., 2024), teacher-oriented work addresses instructional planning (Muchuweni & Jojo, 2026), assessment frameworks address construct validity (Singh et al., 2026), and human-AI synergy models emphasise professional collaboration (Hu, 2026). Technology-mediated learner autonomy, in turn, specifies which responsibilities must remain attributable to the learner.

5.2 Interdependence Without Conceptual Collapse

The five operational dimensions are interdependent but non-equivalent:

- Goal-setting autonomy concerns purpose;
- Prompting agency concerns cognitive delegation;
- Critical verification concerns epistemic warrant;
- Metacognitive regulation concerns understanding and dependence; and
- Ethical accountability concerns legitimacy and attribution.

This distinction prevents conceptual collapse. A learner may possess sophisticated AI literacy while delegating the central reasoning of an assignment, disclose AI use while lacking understanding of the submitted argument, or self-regulate effort while failing to verify a fabricated source. No single neighbouring construct, therefore, captures the complete responsibility structure.

Algorithmic uncertainty and bias make critical verification especially important. Generated outputs may be fluent yet inaccurate, fabricated, incomplete or biased (Holmes & Miao, 2023; Kasneci et al., 2023; Yan et al., 2024). Verification should, therefore, compare claims with disciplinary evidence, inspect source provenance, consider omissions or privileged perspectives, and remain open to rejection.

Human judgement preservation operates at a different level: it enquires whether prompting, verification, self-regulation and ethical decisions remain meaningfully learner directed. Its key criterion is contestability. Reasoned rejection, substantial revision or deliberate restriction of AI assistance can provide stronger evidence of retained judgement than acceptance alone, which may reflect either informed evaluation or passive reliance.

5.3 Human Feedback, Peer Interaction, and Dependence

Technology-mediated autonomy should not be interpreted as a closed learner-AI interaction. Human feedback remains important because judgement develops through comparison, dialogue, challenge and action on feedback (Boud & Molloy, 2013; Carless & Boud, 2018). Generative AI can provide immediate feedback, but reliance on a single system may create a closed evaluative loop in which the same

technology contributes to production, critique and revision. Peer discussion, educator feedback, oral questioning and disciplinary dialogue provide independent calibration and can expose hidden assumptions when students explain AI-supported decisions or critique verification processes. The framework, therefore, supports human-AI-human learning sequences rather than substitution of peer and teacher dialogue.

Dependence is treated primarily as a metacognitive and regulatory problem. Student reliance and resistance are not binary (F. Wang et al., 2025), however, the corpus does not justify a separate dimension for affective dependence, such as reassurance-seeking or discomfort about working without AI. These possibilities require empirical study.

5.4 Practical and Assessment Implications

Pedagogical and assessment responses to generative AI in higher education should move beyond detecting whether AI was used. The more important question is whether learning and assessment practices make learner responsibility visible. Assessment should align AI use with the construct being assessed. If the intended construct is independent disciplinary reasoning, AI-generated reasoning may weaken the validity of the evidence.

If critical human-AI collaboration is itself a learning outcome, AI use may be legitimate or necessary when students demonstrate verification, decision-making, transparent attribution and final responsibility (Bearman & Ajjawi, 2023; Perkins et al., 2024). This argument implies a shift from exclusive reliance on polished final products towards selected process evidence. Exhaustive surveillance is unnecessary; instead, educators can, when learner responsibility matters, request concise evidence such as a pre-task AI-use plan, selected prompt annotations, verification notes, rejected output with reasons, revision rationale, disclosure statements, oral defence or brief reconstruction of reasoning without AI assistance.

Such process evidence is not self-authenticating: Prompt logs, declarations and revision records may be incomplete or selectively curated, and their validity depends on alignment with the construct being assessed. A practical decision rule is that the more central a delegated intellectual function is to the assessed construct, the stronger the evidence required that the learner could reconstruct, verify and defend the resulting reasoning.

Table 6 translates the conceptual findings into pedagogical and assessment design principles. The table is intended as a set of decision aids rather than a universal scoring rubric.

Table 6: Translating technology-mediated learner autonomy into pedagogical and assessment practice

Framework element	Assessment design principle	Possible evidence	Lower-resource alternative
Human judgement preservation	Require learners to justify consequential academic decisions rather than to submit a product alone	Brief decision rationale, oral defence, explanation of accepted and rejected AI suggestions	Two or three targeted oral questions or a justification written in-class
Goal-setting autonomy	Make the intended purpose and permitted role of AI explicit	Short AI-use plan; statement of learning goals and assistance boundaries	One paragraph submitted with the task
Prompting agency	Assess whether AI interaction supports rather than replaces target reasoning	Selected annotated prompts showing refinement and limits	Ask learners to submit only one or two consequential prompts
Critical verification	Require evidence that substantive AI claims have been checked	Source comparison, correction log, examples of rejected output	Verify one selected AI claim against an authorised source
Metacognitive regulation	Ask learners to evaluate how AI affected their understanding and dependence	Brief reflection identifying misunderstanding, strategy change, or excessive reliance	Short post-task reflection or viva question
Ethical accountability	Align disclosure requirements with institutional rules and task expectations	AI-use declaration and description of substantive contribution	Standardised declaration with a small number of response fields

Note. These examples should be adapted to disciplinary outcomes, assessment stakes, privacy requirements and available staff resources. They are not intended to mandate full prompt-history surveillance.

Evidence of autonomy should remain discipline sensitive. Humanities students could defend interpretations against scholarly sources; Science, technology, engineering and mathematics (STEM) students could be required to reconstruct solution logic or identify errors; and health or professional programmes could use simulations, oral reasoning, case justification or supervised application when judgement has real-world consequences. Process evidence can increase workload and create privacy concerns if complete prompt histories are collected unnecessarily. Institutions should target high-stakes points where evidence of reasoning, verification or authorship is educationally necessary instead of requiring exhaustive documentation.

5.5 Institutional and Contextual Implications

Technology-mediated autonomy cannot be produced by learner effort alone. Educator scaffolding, assessment design, institutional policy, disciplinary norms, access and digital conditions function as enabling or constraining conditions rather than learner-level dimensions. Institutions should clarify levels of acceptable AI involvement rather than rely on a single permitted/prohibited rule; they should specify expectations for brainstorming, explanation, feedback, editing, coding assistance, drafting, source discovery and substantive generation (Chan, 2023; Holmes & Miao, 2023; Moorhouse et al., 2023). Staff development should extend beyond technical AI training, to task design, verification, disclosure, authorship disputes and the distinction between scaffolding and substitution. Students should also participate in developing AI-use guidance, so that institutions can identify ambiguous, impractical, inequitable or inconsistent rules (Chan & Hu, 2023).

Context matters. Studies in Ghana and Palestine highlight the importance of literacy, access, pedagogical support and local conditions (Essel et al., 2026; Hamamra et al., 2026). Unequal access, the language-related needs of multilingual learners, disciplinary norms and institutional capacity may affect how the dimensions can be demonstrated. For multilingual learners, language assistance could reduce barriers without replacing disciplinary reasoning; assessment should differentiate between support for expression and delegation of the construct being assessed. The framework, therefore, provides a shared conceptual language rather than a universal prescription. Institutions can adapt implementation while preserving the question of which responsibilities should remain with the learner.

5.6 Limitations and Future Research

The framework is conceptual rather than empirically validated; its mechanisms, dimensions, and normative core should not yet be interpreted as a factor structure, measurement instrument or causal model. The bounded integrative corpus prioritises theoretical relevance and cross-domain synthesis rather than exhaustive coverage. Broader database searches may identify additional perspectives, and the absence of independent dual screening or coding limits procedural reproducibility.

The framework was developed primarily for higher education; application to schools, vocational training, clinical education, workplace learning or professional practice may require modification. The distinction between the five dimensions and human judgement preservation remains conceptual. Future research should test dimensional boundaries and relationships with established measures of autonomy, self-regulation, AI literacy and academic integrity, and examine whether human judgement is best modelled as a higher-order principle, boundary condition, outcome or observable capability.

Qualitative, longitudinal and intervention research should test support-substitution boundaries using interviews, stimulated recall, prompt and revision traces, verification tasks, oral defence and targeted pedagogies. Cross-cultural and cross-disciplinary studies, especially in resource-constrained and

multilingual settings, are needed to test contextual boundaries. Further work should examine affective dependence, peer-AI-human dialogue, disciplinary forms of judgement and responsibility when AI is embedded invisibly in ordinary educational software.

6. Conclusion

This conceptual study argues that generative AI does not make learner autonomy obsolete; rather, it changes the conditions under which autonomy must be exercised and evidenced in higher education. The analysis identifies three mechanisms through which this reconfiguration occurs – cognitive redistribution, authorship ambiguity and regulatory intensification – and develops technology-mediated learner autonomy as a learner-level responsibility structure for responding to these changes. The framework comprises five operational dimensions: goal-setting autonomy, prompting agency, critical verification, metacognitive regulation and ethical accountability. These dimensions are organised around human judgement preservation as a normative core rather than a sixth equivalent component.

The contribution of the framework lies in specifying what should remain attributable to the learner when generative AI participates in academic work. Autonomy is, therefore, not equated with working without AI, nor can it be inferred from product quality, technical AI competence or disclosure alone. It is better evidenced through purposeful control of AI assistance, verification of generated content, monitoring of understanding and dependence, responsible authorship and the capacity to revise, reject and defend final academic decisions. Because the framework is conceptual and grounded in a bounded integrative literature corpus, its components and relationships require empirical validation across disciplines, institutions and cultural contexts. For higher education, the immediate implication is to design learning, assessment and institutional guidance that make learner responsibility and final judgement visible, rather than treating AI use itself as the primary education problem.

Conflict of Interest

The authors declare that they have no conflict of interest.

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