

Two Pathways, One Tool: The Psychological Consequences of Generative AI Use Among University Students

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Abstract

Generative artificial intelligence (GenAI) has been adopted by university students faster than any previous educational technology, yet evidence on its psychological consequences remains fragmented and apparently contradictory. Some studies report gains in motivation, self-efficacy and well-being; others report anxiety, procrastination, cognitive offloading and dependence. This paper reconciles these findings through an integrative review of 55 scholarly sources drawn from educational technology, educational psychology and information systems research. Drawing on self-determination theory, cognitive load theory, self-regulated learning theory and the technostress paradigm, a Dual-Pathway Model of GenAI use is proposed. The model holds that psychological consequences are determined not by the volume of use but by the mode of engagement. An augmentation mode, in which GenAI is used as a tutor and thinking partner, initiates an empowerment pathway marked by need satisfaction, academic self-efficacy and eudaimonic well-being. A dependence mode, in which GenAI substitutes for the student's own cognitive effort, initiates an erosion pathway marked by cognitive offloading, integrity anxiety, skill-atrophy perception, procrastination and diminished self-worth. The two modes are specified as continuous, episodic states rather than fixed user types and adaptive cognitive offloading is distinguished from maladaptive cognitive outsourcing. Both pathways are self-reinforcing and their divergence is moderated by AI literacy, self-regulated learning skill and institutional guidance. Eight testable propositions are derived, each annotated for evidential status, together with implications for students, educators, counsellors and policymakers. The model reframes an apparent empirical contradiction as unmeasured moderation and offers a testable structure for future enquiry.

Keywords: ChatGPT, Cognitive Offloading, Generative Artificial Intelligence, Higher Education, Psychological Well-being, University Students.

Introduction

The public release of large language model applications marked a decisive turning point in the relationship between students and technology. Within months, generative artificial intelligence (GenAI) tools had permeated nearly every dimension of university life, from drafting essays and debugging code to summarising readings, generating study plans and providing informal emotional support (1, 2). Unlike earlier educational technologies, which mediated access to information, GenAI produces the intellectual artefacts of learning itself: text, arguments, explanations and solutions. It can therefore act as an endlessly patient tutor that scaffolds understanding, or as an effortless substitute that completes the very tasks through which understanding is built (3). Artificial intelligence in education long predates GenAI, but earlier systems were designed and deployed by institutions; GenAI inverted that arrangement, placing a general-

purpose cognitive assistant in students' own hands, adopted individually, used privately and largely invisible to instructors (4–7). The stakes are high for university students, a population already characterised by elevated stress, identity formation pressures and evaluation anxiety and among whom counselling needs have risen in the post-pandemic period (8, 9). The evidence accumulated since this shift divides sharply. One stream documents substantial benefit. Quasi-experimental work in programming education reports gains in computational thinking, programming self-efficacy and motivation where support is scaffolded (10); meta-analytic synthesis of chatbot studies reports moderate positive pooled effects on learning outcomes and motivation, strongest for short and well-structured interventions (11) and perception studies report that students value continuous explanation, personalised feedback and reduced

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embarrassment when asking basic questions (12). Reviews across disciplines converge on a common verdict that the technology offers substantial pedagogical promise alongside substantial risk to integrity and skill development (13, 14). A second stream documents costs of comparable magnitude. Time-lagged survey evidence links heavier use to procrastination, self-reported memory impairment and lower grade performance (15), randomised evidence shows that students fail to sustain self-regulated learning behaviours once AI assistance is withdrawn (3); and a pre-GenAI literature had already established that reliable external information sources reduce internal retention (16), that the mere availability of a connected device taxes working memory (17) and that habitual offloading reshapes what people attempt to remember or compute unaided (18).

Four theoretical traditions bear directly on this divergence. Self-determination theory holds that well-being flows from the satisfaction of needs for competence, autonomy and relatedness (19, 20); GenAI can generate authentic mastery experiences or remove the struggle from which competence perceptions grow and mastery experience is the strongest source of self-efficacy (21, 22). Cognitive load theory distinguishes intrinsic, extraneous and germane load (23–25); GenAI can strip away extraneous load, but it can equally strip away the germane processing that builds schemas and the learning sciences warn that removing productive struggle undermines durable learning (26, 27). Self-regulated learning theory describes the forethought, monitoring and reflection cycle through which effective learners govern their study (28); GenAI can support that cycle or collapse it and weak self-regulation is the core of procrastination (29, 30). The technostress paradigm and transactional stress theory explain how the technology itself becomes a stressor, as students appraise regulatory uncertainty, detection fear and pressure to keep pace with AI-fluent peers against their coping resources (31–35).

Three limitations are common to both empirical streams. The literature is outcome-fragmented: individual studies measure motivation, or procrastination, or anxiety, or performance, but rarely situate these outcomes within a common causal architecture. It is direction-fragmented: positive and negative findings accumulate in

parallel streams that seldom cite one another, producing an appearance of contradiction. Most consequentially, almost none of the primary studies measured how students engaged with the tool, that is, whether GenAI amplified or replaced their own cognitive work. Positive-stream studies typically examined structured, scaffolded, instructor-mediated use, while negative-stream studies typically examined unsupervised, pressure driven use. Policy scholarship on academic integrity has meanwhile developed largely separately from the psychological literature (36–38), even though integrity anxiety is itself a psychological outcome.

The research gap is therefore neither an absence of evidence nor a genuine empirical conflict, but the absence of an integrative framework specifying the mechanism through which a single technology generates opposite psychological trajectories in the same population. Accordingly, this paper develops a Dual-Pathway Model of the psychological consequences of GenAI use among university students. Three objectives follow: to synthesize the fragmented empirical literature on those consequences; to integrate the four theoretical traditions above into a single explanatory model; and to derive testable propositions and practical recommendations for students, educators, counsellors and institutional policymakers. The guiding questions are through which psychological mechanisms GenAI use enhances or erodes student well-being, which factors determine whether a student follows the beneficial or the harmful pathway and what institutions can do to shift students towards the beneficial one.

The novelty of the study lies in three moves. It reframes an apparent empirical contradiction as unmeasured moderation, identifying engagement mode as the missing variable that renders the field's heterogeneity systematic rather than merely conflicting. It distinguishes adaptive cognitive offloading from maladaptive cognitive outsourcing, a distinction that prevents the conflation of all reliance on external cognitive tools with harm. And it specifies augmentation and dependence not as fixed user types but as continuous, episodic states of engagement, so that the resulting propositions are testable at the level of the individual use episode rather than the individual student.

Methodology

This paper adopts an integrative conceptual review design, an approach suited to a research area that is empirically active but theoretically fragmented and whose purpose is not to estimate an effect size but to critique, synthesise and reorganise existing knowledge into a new theoretical structure from which testable propositions can be derived (39, 40). Reviews of this kind are recognised as a distinct methodological genre with their own standards of rigour, in which the contribution is judged by the explanatory value of the resulting framework rather than by the precision of a pooled estimate (41–43). Because the design is explanatory rather than aggregative, no pooled effect estimate was attempted and no meta-analytic weighting was applied. The procedural reporting set out below is nonetheless adapted from systematic review practice, following the reporting logic of the PRISMA 2020 statement, so that the selection process is transparent and auditable (44).

Three databases were searched. Scopus and Web of Science were selected for their indexed coverage of educational technology, educational psychology and information systems; Google Scholar was searched additionally to capture recent GenAI scholarship not yet fully indexed in the subscription databases. Searches combined three concept blocks using Boolean operators, with truncation and title–abstract–keyword field limits applied in Scopus and Web of Science. The technology block comprised “generative AI” OR “generative artificial intelligence” OR ChatGPT OR “large language model*” OR “AI chatbot*”. The population and setting block comprised “university student*” OR undergraduate* OR postgraduate* OR “higher education” OR “tertiary education”. The psychological construct block comprised well-being OR wellbeing OR “mental health” OR self-efficacy OR motivation OR anxiety OR stress OR technostress OR dependence OR over-reliance OR procrastination OR “cognitive offloading” OR “academic integrity”. The three blocks were combined with the AND operator. Backward citation chaining was then performed on the reference lists of all retrieved reviews and meta-analyses in order to identify sources the database searches had missed, a standard supplement to database searching in review work of this type (45).

Searching for GenAI-specific evidence was restricted to material published from November 2022, the point at which conversational large language model applications entered mass public use. Two supplementary searches were run without this restriction in order to retrieve, first, precursor evidence on digital cognition, cognitive offloading and technology-related well-being published between 2011 and 2020 and, second, the foundational theoretical and psychometric works published between 1976 and 2008 that were cited repeatedly across the screened studies. The retained corpus therefore spans 1976 to 2025 by design, a layered temporal structure that allows a new phenomenon to be interpreted against mature theory rather than in an interpretive vacuum.

Sources were included if they addressed GenAI or a directly relevant precursor technology; concerned university students or reported theoretical mechanisms demonstrably applicable to them; reported psychological constructs, mechanisms or outcomes; and were published in English in a peer-reviewed journal, an edited scholarly volume or archival conference proceedings. Sources were excluded if they were purely technical treatments of model architecture or performance without psychological or educational content; concerned school-age populations without theoretical mechanisms transferable to higher education; were unstructured opinion pieces lacking either data or an articulated framework; were unavailable in English; or reported the same dataset as another retained source, in which case the fullest report was retained and the duplicate removed.

Screening proceeded in four stages. At the identification stage, records retrieved from the three databases and from citation chaining were exported to a reference manager and de-duplicated. At the screening stage, titles and abstracts were assessed against the inclusion and exclusion criteria and records failing any criterion were removed. At the eligibility stage, the full texts of the remaining records were read and assessed and sources that did not report a psychological construct, mechanism or outcome on closer reading were excluded. At the anchoring stage, foundational theoretical and psychometric works cited repeatedly across the retained studies were

added in order to ground the emerging model in established theory. Screening decisions were recorded in a spreadsheet together with the reason for each exclusion, providing an audit trail for the selection process. Both authors screened independently at the eligibility stage and disagreements were resolved by discussion until consensus was reached. The final corpus comprised 55 sources; methodological and reporting works cited in this section guided the review procedure and are listed in the references but do not form part of that corpus.

Because the corpus is deliberately heterogeneous in design and genre, appraisal criteria were matched to source type rather than applied through a single instrument, consistent with appraisal practice for bodies of evidence of mixed design (46). Empirical studies were appraised on research design, with longitudinal, randomised and time-lagged designs weighted above cross-sectional ones; on sampling and sample size; on the transparency and psychometric adequacy of measurement; and on the fit between analysis and the inferences drawn. Reviews and meta-analyses were appraised on the transparency of their search and selection procedures and the consistency between evidence and conclusions. Conceptual works were appraised on argumentative coherence, explicitness of assumptions and standing within their tradition. Appraisal was used to weight evidence rather than to exclude sources: a source judged methodologically weaker could illustrate a mechanism or contribute a construct

definition, but was not permitted to carry a proposition on its own.

Analysis proceeded through thematic synthesis (47, 48). Findings from each source were coded as indicating beneficial, harmful or conditional psychological consequences and the stated or implied mechanism for each finding was extracted. Recurring mechanisms were then clustered and mapped onto the four theoretical traditions identified above. The Dual-Pathway Model emerged from the observation that virtually every beneficial finding involved GenAI amplifying student cognition, while virtually every harmful finding involved GenAI replacing it. Trustworthiness was addressed through three practices adapted to conceptual synthesis. An audit trail linked every element of the emerging model to the specific sources supporting it. Negative-case analysis was performed, in which the corpus was deliberately interrogated for evidence of harmful augmentation-mode use and beneficial dependence-mode use, the combinations the model does not predict. Coding continued to conceptual saturation, the point at which additional sources reproduced mechanisms already represented in the framework without adding new ones. Table 1 presents representative studies from the corpus and the pathway each implicates. As the study is an integrative review of previously published literature, it involved no human or animal participants and ethical approval was therefore not required.

Table 1: Representative Studies on the Psychological Consequences of Generative AI Use

Context and Design	Key Psychological Findings	Pathway Implicated	References
Two-wave time-lagged survey, university students, Pakistan	Workload and time pressure predicted use; heavier use predicted procrastination, memory impairment and lower CGPA	Erosion	(15)
Survey, 399 students, Hong Kong	Valued personalised support and feedback, but concerned about accuracy, over-reliance and personal development	Both (conditional)	(12)
Quasi-experiment, programming students, Türkiye	AI-supported group higher on computational thinking, self-efficacy and motivation than controls	Empowerment	(10)
Randomised study, 1,625 students	Performance improved while assistance was present; self-regulated behaviours not retained once removed	Erosion	(3)
Multi-method case study of ChatGPT in education	Enthusiasm alongside cheating, over-trust and disrupted study habits; urges responsible-use scaffolds	Both (conditional)	(49)
Policy analysis, higher education	Integrity ambiguity creates anxiety; recommends redesigned assessment and explicit norms	Erosion (moderator)	(36)

Rapid review of 50 early studies	Benefits for personalised learning co-exist with inaccuracy, plagiarism and dependence risks	Both (conditional)	(50)
Meta-analysis of 24 chatbot studies	Moderate positive effects on learning outcomes and motivation, larger for short, structured interventions	Empowerment	(11)
Conceptual analysis, social work education, South Africa	AI can empower practice if values-guided, but risks deskilling without deliberate governance	Both (conditional)	(51)
Comparative survey of counselling needs, Malaysian students (2022–2024)	Post-pandemic counselling needs rose, academic stress prominent; services must anticipate technology-related issues	Context (well-being baseline)	(8)

Results

The Dual-Pathway Model, presented in Figure 1, holds that the psychological consequences of GenAI use are determined by the mode of engagement rather than the amount of use. The model comprises five elements: GenAI use, characterised by frequency, purpose and mode; two engagement modes, augmentation and

dependence; pathway specific psychological mechanisms; adaptive and maladaptive outcomes; and moderators that govern which mode a student adopts. Feedback loops connect outcomes back to subsequent use, rendering both pathways self-reinforcing.

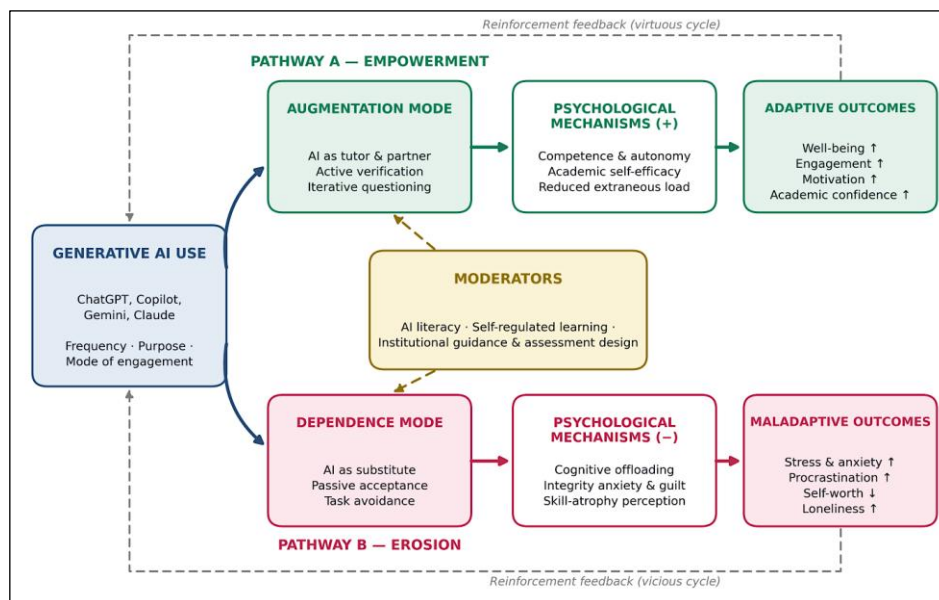


Figure 1: The Dual-pathway Model of the Psychological Consequences of Generative AI Use Among University Students

Three assumptions govern how the model should be read. First, it is mechanism-mediated: raw exposure to GenAI has no direct psychological effect and all consequences flow through the pathway-specific mechanisms, which is why studies operationalising only frequency of use produces inconsistent results. Second, the model is episodic and dimensional rather than typological. Augmentation and dependence are properties of individual use episodes, not fixed traits of students and are better represented as two continuous dimensions of engagement than as a single bipolar axis or as two categories of user. A student may

work Socratically in a subject she loves on Monday and delegate an assignment wholesale in a subject she fears on Thursday and a single episode may score appreciably on both dimensions. Person-level position is therefore an aggregate over episodes rather than a category membership and it is this distribution that the moderators shift. Third, the model is dynamic: outcomes recursively alter the probability of each mode in subsequent episodes, which is what makes both pathways self-reinforcing and gives early habits their outsized importance.

Because the model combines empirical synthesis with theoretical inference, the status of its claims requires explicit statement. Evidence-supported associations are relationships for which the corpus contains direct empirical observation, including the association between heavier, pressure-driven use and procrastination, self-reported memory impairment and lower grades (15), the failure of self-regulated learning behaviours to persist once assistance is withdrawn (3), the association between scaffolded, attempt-first support and gains in self-efficacy and motivation (10, 11) and the co-occurrence of valued support with over-reliance concerns in the same student populations (12). These associations are correlational or, at most, quasi-experimental and none establishes the direction of causation with confidence. Postulated causal mechanisms are the explanatory links the

model supplies to connect them: that delegation produces distress by eliminating the mastery experience, that skill-atrophy perception attacks the competence need directly, that integrity anxiety functions as a technostressor and that both pathways are self-reinforcing through recursive feedback. These are inferences from established theory (18, 19, 26, 34) applied to observations that were not designed to test them; they are plausible and internally consistent, but they remain untested as mechanisms. Boundary and scope claims are analytic stipulations rather than findings. Throughout, associations are reported as associations, mechanisms are introduced with explicitly hypothetical phrasing and each proposition is annotated with the strength of the evidence currently supporting it. Table 2 defines the model's constructs.

Table 2: Constructs and Working Definitions in the Dual-pathway Model

Construct	Working Definition	Theoretical Root	References
Augmentation mode	A state of engagement in which GenAI amplifies the student's own cognition: explaining, questioning, quizzing and giving feedback while the student remains the author of the work	Distributed cognition; scaffolding	(52, 53)
Dependence mode	A state of engagement in which GenAI substitutes for the student's cognition: producing work the student submits or accepts with minimal processing	Cognitive offloading; transactive memory	(16, 18)
Adaptive offloading	Externalisation of cognitive operations that the task is not designed to develop, releasing capacity for germane processing	Cognitive load theory	(23, 24)
Maladaptive outsourcing	Externalisation of precisely the cognitive operations the task exists to develop, pre-empting schema formation	Desirable difficulties; guidance	(26, 27)
Need satisfaction	Fulfilment of competence, autonomy and relatedness needs during study	Self-determination theory	(19, 20)
Academic self-efficacy	Belief in one's capability to organise and execute academic tasks	Social cognitive theory	(21, 22)
Cognitive offloading	Delegation of cognitive work to an external tool, reducing internal processing	Cognitive offloading	(18)
Integrity anxiety	Apprehension arising from uncertainty about the legitimacy and detectability of AI-assisted work	Academic integrity; technostress	(34, 36)
Skill-atrophy perception	The student's belief that unaided abilities are deteriorating through disuse	Desirable difficulties	(17, 26)
Psychological well-being	Hedonic satisfaction and eudaimonic functioning, including self-worth and mastery	Hedonic and eudaimonic traditions	(54, 55)

In the augmentation mode the student retains epistemic agency. GenAI is prompted to explain, to test, to critique drafts the student has written and to model expert reasoning the student then imitates, in the manner of classical scaffolding (52). Three mechanisms are hypothesised to convert this mode into well-being. The first is need satisfaction: because the student ultimately

performs the task, successes register as authentic mastery experiences that satisfy the competence need, while self-directed inquiry satisfies autonomy (19, 20). The second is self-efficacy growth: repeated mastery experiences are the strongest source of efficacy beliefs (21) and structured GenAI support raises programming self-efficacy and motivation (10). The third is load

optimization: GenAI removes extraneous load while preserving the germane load, the productive struggle that builds schemas (23, 24).

The well-being generated by this pathway is primarily eudaimonic rather than hedonic. What the pathway produces directly are the components of eudaimonic functioning: environmental mastery, through demonstrated competence on tasks the student has actually performed; autonomy, through self-directed inquiry; and personal growth, through the accumulation of capability across episodes (55). Hedonic well-being, in the sense of life satisfaction and positive affective balance (54), is predicted to follow as a downstream consequence of these gains rather than as the pathway's proximal output. The specification is not merely terminological, because it carries a discriminant prediction. The erosion pathway can also raise hedonic indicators in the short term, since delegation reliably produces relief from deadline pressure and evaluation anxiety. A study relying on affect or life-satisfaction measures alone therefore cannot distinguish the two pathways and may find both associated with improved well-being. Eudaimonic measures should separate them, because relief from an avoided task generates no mastery, no autonomy and no growth.

The downstream outcomes are the adaptive cluster documented in the optimistic stream of the literature: higher engagement and motivation, reduced fear of difficult subjects, greater academic confidence and improved well-being (11, 50, 56). Consistent with broaden-and-build theory, the positive emotions generated along this pathway are hypothesised to broaden students' thinking and build lasting resources, including increasingly sophisticated strategies for using the tool itself (57). Expert-informed learning-design work on student-AI collaboration describes this configuration directly, specifying how AI can act as an instructional scaffold and learning mate that supports, rather than substitutes for, the learner's own inquiry (58). A concrete episode illustrates the mode. A student drafts her own thesis and outline unaided, asks the model to attack the argument and interrogate her evidence, writes the essay herself, submits her draft for critique and finishes by generating a self-test. Every element preserves her authorship, so successes are attributable to herself and register as mastery experiences; the interrogation deepens rather than

replaces her processing, preserving germane load; and judging suggestions that are sometimes wrong trains the critical skill that AI literacy scholars identify as central (59, 60).

In the dependence mode, epistemic agency is transferred to the machine. The trigger is typically not laziness but pressure: heavy workloads, deadline congestion and evaluation fear make wholesale delegation appear rational (15, 61). Three mechanisms are hypothesised to convert delegation into distress. The first is cognitive offloading: the reasoning and production work is done externally, so no schema is built and no mastery experience occurs (18) and what is reliably outsourced ceases to be internally maintained (16, 17). The second is integrity anxiety and guilt: because institutional norms remain ambiguous, students who submit AI-produced work experience chronic apprehension about detection and legitimacy, a textbook technostress condition (34, 36, 37). The third is skill-atrophy perception: students notice that unaided work feels harder than before and this perception attacks the competence need and self-worth (26, 55).

The downstream outcomes are the maladaptive cluster: procrastination, since the ability to generate work instantly removes the deadline pressure that normally curbs delay (29, 30); anxiety and stress; declining perceived and actual performance (15); and a creeping sense of fraudulence in one's own credentials. Each consequence is expected to increase the appeal of further delegation, since weakened skills and postponed work make the next unaided task more aversive, closing the vicious cycle shown in Figure 2. The model further specifies a three-stage temporal drift. In the first stage, delegation is episodic, deployed under acute deadline pressure and experienced as relief, so cross-sectional measurement detects little. In the second, use hybridises: the model produces the skeleton and the student edits, authorship becomes ambiguous and integrity anxiety and intermittent guilt first appear (36). In the third, delegation becomes the default and unaided work becomes actively aversive because atrophied skills make it slower and more punishing; task aversiveness is among the strongest proximal causes of procrastination (29) and the mood repair that delegation provides mirrors the emotion-regulation dynamics

documented in that literature (30). This explains an otherwise puzzling feature of the evidence: early-adoption snapshots find negligible harm

while time-lagged designs detect it clearly (15). The erosion pathway incubates.

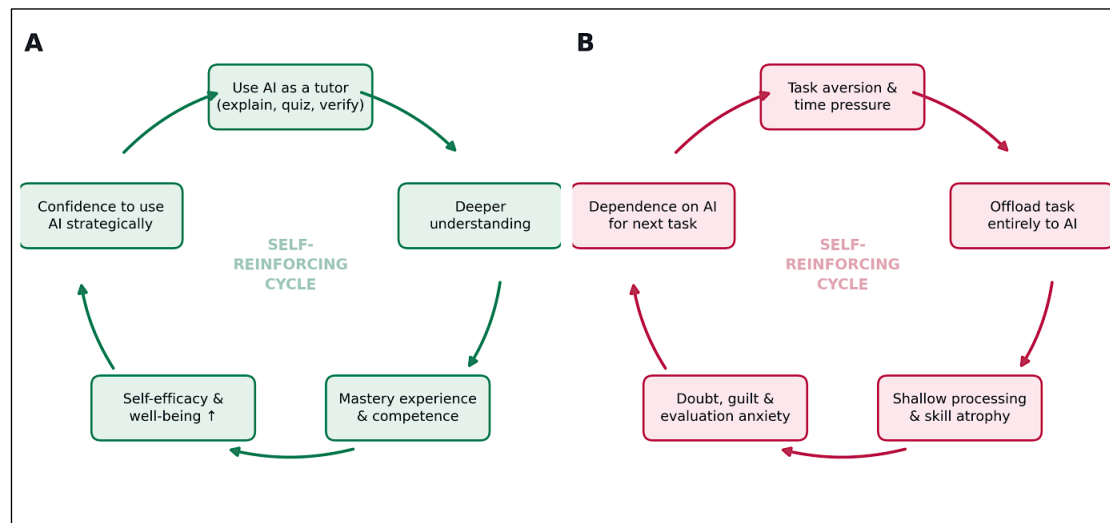


Figure 2: Self-Reinforcing Dynamics of the Two Pathways. (A) The Virtuous Cycle of the Empowerment Pathway, (B) The Vicious Cycle of the Erosion Pathway

The model would be untenable if it treated all reliance on external cognitive tools as detrimental. Human cognition has always been distributed across notebooks, calculators, reference works and colleagues and the offloading literature is explicit that externalising cognition is frequently rational and performance-enhancing (18). A distinction is therefore required between adaptive cognitive offloading and maladaptive cognitive outsourcing. The criterion that separates them is not the presence of external support, nor its quantity, but the relation between what is externalised and the learning objective of the task. Offloading is adaptive when what is externalised is not what the task exists to develop: delegating the arithmetic in a statistics assignment whose objective is interpretation, the formatting of a reference list or the transcription of an interview removes extraneous load and releases capacity for the germane processing that builds schemas (23, 24). It is also adaptive when it operates as a scaffold that is progressively withdrawn as competence develops (52) and when the student retains the capacity to perform the offloaded operation unaided should the tool become unavailable. Outsourcing is maladaptive when the externalised operation is precisely the operation the task was designed to train: delegating the construction of an argument in a course whose objective is argumentation, or the debugging of code in a course whose objective is debugging, removes the

germane load itself, so no schema is built and no mastery experience is available to register (26, 27). Three markers distinguish the maladaptive case in practice: the offloaded operation coincides with the assessed learning objective; the student could not currently perform that operation unaided; and the delegation is concealed rather than declared. Novices are therefore structurally more exposed than advanced students and the same observable behaviour can change category as expertise develops, since a statistician delegating routine code generation is offloading adaptively whereas a first-year student delegating the same code is outsourcing the skill the course is meant to instil. The harm lies neither in the tool nor in the act of externalising cognition, but in the coincidence between what is externalised and what the task is meant to develop.

Because engagement mode is the pivotal construct of the model, it must be specifiable at the level of observable behaviour rather than inferred from attitudes or self-described intentions. Table 3 sets out behaviours that differentiate augmentation from dependence. Each is stated at the level of the individual use episode and is, in principle, recoverable from prompt logs, from experience-sampling reports or from purpose inventories, which makes the construct measurable rather than merely interpretive. Augmentation is marked by behaviours that keep the student inside the cognitive loop, whereas dependence is marked by

behaviours that remove the student from it. The list is diagnostic rather than exhaustive and two qualifications follow from the dimensional specification above. Most real episodes contain behaviors of both kinds, so an episode is characterised by the balance of markers present rather than by a single decisive act. And because the adaptive-offloading distinction is task-relative,

the same marker can carry different weight in different courses: requesting a finished translation is dependence in a language course and adaptive offloading in a chemistry course. Coding schemes derived from Table 3 should therefore be applied together with information about the assessed learning objective.

Table 3: Observable Behavioral Markers Differentiating Augmentation from Dependence within a Use Episode

Observable Behaviour in a Use Episode	Mode Indicated	What the Behaviour Reveals	References
Requesting explanation of a concept the student is attempting to understand	Augmentation	Student retains the problem; extraneous rather than germane load is reduced	(23, 24)
Submitting a draft already written, for critique or feedback	Augmentation	Authorship retained; the model evaluates rather than produces	(52, 53)
Requesting alternatives or counter-arguments to compare against one's own	Augmentation	Student performs the evaluative work, itself a trained skill	(59, 60)
Verifying the model's reasoning against a source or one's own working	Augmentation	Output is treated as a claim, not an answer	(59, 60)
Iterative questioning that progressively narrows a problem	Augmentation	Forethought and monitoring phases of self-regulation stay active	(28)
Consulting the model only after an independent attempt	Augmentation	Productive struggle precedes assistance, preserving mastery	(26, 52)
Issuing a single prompt requesting the finished artefact	Dependence	The operation the task exists to train is externalised in full	(16, 18)
Accepting output with minimal reading, revision or verification	Dependence	Little processing occurs, so no schema is built	(18)
Submitting model output as one's own without declaration	Dependence	Concealment generates integrity anxiety regardless of detection	(36, 37)
Delegating an operation never performed unaided	Dependence	Skill formation is pre-empted rather than supplemented	(26, 27)
Using the model to avoid beginning, not to progress from a beginning	Dependence	Delegation acts as short-term mood repair, the signature of procrastination	(29, 30)

Five moderators govern which mode a student adopts. Students who understand what large language models are, how they err and how to prompt them critically are far better positioned to use them as instruments rather than oracles (59, 60); AI literacy converts the tool from an answer machine into a thinking partner. Strong self-regulators possess the forethought and monitoring habits needed to keep themselves in the loop (28), whereas weak self-regulators, who are also the students most prone to procrastination (29), are precisely those most likely to slide into dependence when a delegation-capable tool is available. Clear, teachable institutional policies reduce integrity anxiety and legitimise augmentation-mode use, whereas blanket

prohibition drives use underground where it defaults to dependence (36, 38, 62); assessment that rewards process, oral defence and in-situ performance structurally removes the payoff of delegation (37) and comparable arguments for deliberate, values-led governance of AI adoption have been made in professional education (51). Cross-national analysis of generative AI policies and guidelines at 40 universities across six global regions supports this emphasis, showing that institutions anchor responsible adoption in academic integrity provisions and clearly defined roles and responsibilities for staff, students and administrators (63). Motivational orientation determines which affordance of the tool is psychologically salient: autonomously motivated

students approach GenAI as a means of understanding, whereas students driven by fear of failure approach it as a means of escape (19, 20) and control-value theory sharpens the prediction, since a task appraised as important but uncontrollable generates anxiety for which delegation is the fastest available route to restoring a sense of control (9). Finally, prior knowledge matters, because novices lacking domain schemas cannot reliably evaluate the model's output, so critical engagement collapses into acceptance (27) and because the foundational skills GenAI can perform for them are exactly the skills their current developmental stage exists to build (26), whereas advanced students can

delegate routine components while retaining the expertise to supervise the output (53).

Table 4 summarises the model as eight propositions suitable for empirical testing with established instruments, including basic-need-satisfaction scales (20), academic self-efficacy measures adapted from computer self-efficacy work (22), technostress inventories (34) and well-being measures (54, 55). Each proposition is annotated with the strength of the evidence currently supporting it, so that propositions resting on observed associations are not read as equivalent to propositions resting on theoretical inference alone.

Table 4: Research Propositions Derived from the Dual-pathway Model, with Evidential Status

No.	Proposition	Evidential Status
P1	Augmentation-mode GenAI use is positively related to basic psychological need satisfaction, academic self-efficacy and eudaimonic well-being.	Observed association (10, 11); causal direction untested.
P2	Dependence-mode GenAI use is positively related to cognitive offloading, integrity anxiety and skill-atrophy perception.	Observed association (15,36); offloading link inferred from precursor work (16,18).
P3	Need satisfaction and self-efficacy mediate the positive relationship between augmentation-mode use and eudaimonic well-being.	Postulated mechanism; no mediation test in the corpus.
P4	Offloading, integrity anxiety and skill-atrophy perception mediate the negative relationship between dependence-mode use and psychological well-being.	Postulated mechanism; partly consistent with the chain reported in (15).
P5	Total frequency of GenAI use, considered without mode, has no consistent direct relationship with well-being.	Consistent with existing frequency-based inconsistency; untested directly.
P6	The relationships in P1 to P4 strengthen over time, reflecting the self-reinforcing feedback loops of both pathways.	Postulated; requires cross-lagged data unavailable in the corpus.
P7	AI literacy and self-regulated learning skill increase the likelihood of augmentation-mode use and buffer the harms of dependence-mode use.	Postulated moderation; constructs well defined (28, 59, 60) but untested as moderators.
P8	Clear institutional guidance and process-oriented assessment design reduce dependence-mode use and integrity anxiety at the cohort level.	Postulated; policy arguments exist (36, 38) but no intervention estimates the effect.

Four boundary conditions delimit the model's claims. Its population scope is university students engaged in assessed academic work, where evaluation, credentials and identity-relevant competence are central (9). Its technological scope is general-purpose conversational GenAI used for text-centric tasks; domain-specific tools embedded in supervised pedagogical designs (4) sit largely outside the dependence-mode risk because their designs constrain delegation. Dependence mode is

a behavioural-functional pattern, not a clinical diagnosis and the model makes no claims about addiction in the psychiatric sense. The model also brackets the relatedness need, since conversational agents invite parasocial dynamics whose consequences for loneliness are potentially profound but analytically separable from the academic mechanisms modelled here. Relatedly, the model does not claim that every pleasant psychological consequence of GenAI use belongs to

the empowerment pathway. Delegation reliably produces immediate affective relief; companionship from a conversational agent may reduce loneliness independently of any learning; and fluent explanation without retrieval or application can produce an illusion of understanding in which subjective confidence rises while unaided capability does not. Psychological outcomes should therefore be evaluated jointly with their educational substrate rather than treated as self-validating and studies reporting well-being gains from GenAI use should specify whether those gains accompany the development of the capability being assessed or substitute for it.

Discussion

The central claim of this paper is that the GenAI literature is not contradictory but under-specified. Once engagement mode is introduced as the pivotal construct, the two streams of findings fall into place as descriptions of two different populations of use episodes. Studies reporting benefits sample augmentation-heavy engagement, typically structured, instructor-guided or intrin-

sically motivated (10, 11). Studies reporting harm sample dependence-heavy engagement, typically pressure-driven and unsupervised (3, 15). The thematic distribution of the reviewed corpus, shown in Figure 3, illustrates that the field has generated roughly equal empirical weight on both sides while investing comparatively little in the integrative theory needed to connect them.

The distribution rewards closer reading. The largest single cluster is theoretical and measurement foundations, reflecting this paper's deliberate anchoring strategy, but among the empirical clusters the weight is nearly symmetrical: sources documenting learning gains, motivation and self-efficacy are matched almost one-for-one by sources documenting dependence, offloading, procrastination, stress and anxiety. The integrity-and-policy cluster remains comparatively small and cites the psychological clusters only sparsely, confirming the disciplinary separation identified above and underscoring the need for frameworks, such as the present one, in which integrity anxiety is treated as a psychological outcome rather than solely a disciplinary problem.

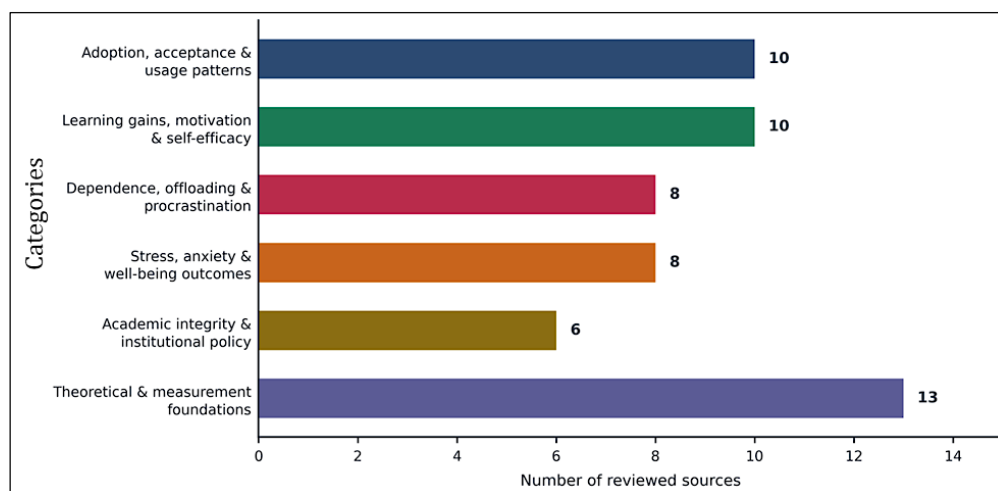


Figure 3: Thematic Distribution of the Reviewed Sources across Six Categories

The claim that divergent findings reflect an unmeasured moderator rather than simple inconsistency requires justification, since any contradictory literature can be rationalised after the fact by positing a hidden variable. Heterogeneity may be considered systematic, rather than merely conflicting, when three conditions hold: the proposed moderator is observable independently of the outcome it is invoked to explain; the direction of findings covaries with that moderator across studies; and

the residual set of findings contradicting the pattern is small and explicable. All three conditions are met in the present corpus. Engagement mode is recoverable from method sections without reference to results, since whether students were required to attempt a task before consulting the tool, whether use was instructor-mediated and whether the model's function was prescribed are reported design features rather than post hoc interpretations. The direction of findings covaries with these features, with beneficial outcomes

reported for structured, scaffolded or pedagogically bounded use (10–12) and harmful outcomes for unsupervised, pressure-driven use (3, 15). And negative-case analysis located few counter-instances: no study reports sustained harm from scaffolded, attempt-first use and none reports durable eudaimonic benefit from wholesale delegation. These conditions are necessary but not sufficient. Design confounding remains plausible, since scaffolded interventions are typically evaluated by researchers invested in their success while unsupervised use is studied by researchers concerned about harm, so engagement mode is confounded with investigator orientation; and the number of primary studies is small enough that the apparent symmetry could reflect sampling variation. The systematic reading advanced here is therefore a defensible interpretation rather than an established finding.

A further question the model must answer directly is how short-term psychological benefits can be congruent with long-term erosion of learning, when the two appear to point in opposite directions. The answer is that they are not competing findings to be reconciled but successive phases of a single reinforcement cycle. The benefits of dependence-mode use are immediate, salient and reliably reinforcing, whereas its costs are delayed, diffuse and rarely attributed to their cause. Relief reinforces the delegation that erodes the capability; the erosion of capability makes the next unaided attempt slower and more aversive; and heightened aversiveness raises the value of further relief. The short-term benefit is therefore not evidence against long-term erosion but the mechanism that produces it, in the same way that the immediate mood repair of procrastination is understood as the proximal cause of its downstream costs rather than as a counterweight to them (29, 30). Methodologically, any design measuring affect and learning in the same wave will find dependence-mode use associated with better affect and poorer learning simultaneously and will appear to yield a paradox; the paradox dissolves under lagged measurement, which is why time-lagged designs detect harm that cross-sectional snapshots miss (15). The model is nonetheless probabilistic rather than deterministic. Moderators shift the likelihood that a given episode is conducted in one mode or the other; they do not fix destinies. A student with weak self-

regulation in an institution with ambiguous policy is at elevated risk of the erosion pathway, not condemned to it.

The model also reframes two ongoing debates. The screen-time debate asked how much technology use is harmful (64, 65), which is the wrong question for GenAI: a student spending three hours in Socratic dialogue and one spending three minutes generating an essay leave similar or inverted footprints on a usage log yet occupy opposite pathways, so measurement must capture mode rather than duration alone. Similarly, the academic integrity debate has largely been conducted in disciplinary terms, as a matter of detection and punishment (36, 37). The model recasts integrity as a psychological variable: ambiguity itself is a stressor and punitive ambiguity pushes anxious students further into concealment and dependence. Integrity policy is thus also mental-health policy. This conclusion aligns with counselling-needs research in the Malaysian context showing that academic and adjustment pressures dominate students' presenting concerns and that services must evolve with the changing sources of those pressures (8). It also complements cross-national policy research, which identifies academic integrity provisions and clearly defined roles and responsibilities as the foundation of responsible institutional GenAI adoption (63); the present model supplies the psychological rationale for that emphasis, since it is the ambiguity of institutional norms, rather than the technology itself, that generates integrity anxiety. Counselling centres should expect and prepare protocols for, presentations in which AI dependence, integrity fear and eroded academic self-worth are intertwined.

The model should also be positioned against the adoption frameworks that dominate educational technology research. The technology acceptance model and its successors explain whether and why students take up a tool (66–68), but end precisely where the psychologically interesting questions begin, being silent on what sustained use does to the user. The Dual-Pathway Model is therefore a post-adoption theory. The two levels connect uncomfortably, since the same utilitarian motives that accelerate adoption are those most likely to instantiate dependence mode, so the factors that make GenAI spread fastest are biased toward its more corrosive mode of use. Finally, the model

connects GenAI to the long theoretical arc of distributed cognition. The distinction between effects with and effects of technology was drawn three decades before large language models existed (53); GenAI is the first mass technology for which the two effects can point in opposite directions with real psychological force. The partnership metaphor remains apt, but partnerships can be developmental or parasitic and the difference lies in who does the growing. Three theoretical contributions follow. The model extends self-determination theory into human-AI interaction by specifying how a single technology can both satisfy and thwart the same needs depending on engagement mode. It extends

cognitive load theory by distinguishing the offloading of extraneous load, which is beneficial, from the offloading of germane load, which is corrosive, a distinction earlier technology rarely forced. And it imports the technostress paradigm into higher education psychology, identifying integrity anxiety as a novel, GenAI-specific technostressor deserving of dedicated measurement. Table 5 translates the model into recommendations for four stakeholder groups. The unifying principle is pathway steering: rather than restricting the tool, institutions should restructure incentives, skills and norms so that augmentation becomes the path of least resistance.

Table 5: Practical Recommendations for Steering Students Toward the Empowerment Pathway

Stakeholder	Recommended Actions
Students	Adopt a draft-first rule: attempt every task unaided before consulting GenAI. Use the tool to question, explain and critique rather than to produce. Self-test periodically without the tool to monitor unaided skill.
Educators	Design assessments that reward process and defence, including drafts, logs, oral examination and in-class performance. Model expert augmentation-mode prompting openly in class. Embed AI-literacy instruction within disciplinary courses.
Counsellors and student affairs	Screen for AI dependence, integrity anxiety and skill-atrophy perception in intake protocols. Frame interventions around competence restoration and self-regulated learning training rather than prohibition.
Polymakers and administrators	Publish clear, teachable AI-use policies distinguishing permitted augmentation from prohibited substitution. Replace detection-and-punishment postures with transparent declaration systems. Invest in institution-wide AI-literacy programmes.

Because the model's pivotal construct has not previously been measured, its operationalisation deserves explicit treatment. Self-report purpose inventories can ask students to allocate recent GenAI use across the concrete behaviours listed in Table 3, from which an augmentation-to-dependence ratio is computed. Experience sampling can capture mode at the episode level, recording what the tool is doing and who is authoring the work. Most powerfully, prompt-log analysis can classify conversation transcripts by authorship locus, providing an objective criterion against which self-report instruments can be validated and large-scale behavioural designs of this kind are already feasible (3). Because self-reports of dependence-mode use are vulnerable to social desirability bias, such triangulation is essential rather than optional. A fourth strategy addresses the interpretive claim above directly: engagement mode can be coded retrospectively from the method sections of published studies, using indicators such as whether an independent

attempt was required before tool use, whether use was instructor-mediated and whether the model's function was prescribed. Entering that code as a moderator in a meta-analysis of psychological outcomes would test formally whether the field's heterogeneity is systematic, converting the present interpretation into a falsifiable claim.

The remaining constructs can draw on established instruments. Need satisfaction is measurable with basic-psychological-needs scales rooted in self-determination theory (19, 20); academic self-efficacy with domain-tailored scales constructed according to established guidelines (21, 22); offloading tendency with the behavioural paradigms of the cognitive-offloading literature (18); technostress with inventories adapted from the organisational tradition (31, 34); and well-being with the Satisfaction with Life Scale and psychological well-being scales (54, 55), the latter treated as the primary outcome for the empowerment pathway for the discriminant reasons set out above. Two constructs, integrity

anxiety and skill-atrophy perception, require new scale development through the standard sequence of qualitative item generation, exploratory and confirmatory factor analysis and tests of measurement invariance. A staged research programme follows from the propositions. Cross-sectional designs with moderation analysis provide first tests of the mode–outcome links and moderator hypotheses. Cross-lagged panel designs across semesters are required for the feedback loops, since reciprocal causation is invisible to single-wave data. Randomised interventions assigning AI-literacy training or process-based assessment redesign provide the strongest tests of the teachable moderators. Linking anonymised counselling-service records with survey and usage data would test the model's clinical predictions, an approach for which Malaysian counselling-needs research provides precedent and infrastructure (8).

Several limitations should be acknowledged. As a conceptual review, the paper proposes rather than tests its model and its propositions await validation. The evidence base is young, predominantly cross-sectional and reliant on self-report, so longer-run dynamics remain unverified and the reading of the field's heterogeneity as systematic remains an interpretation rather than a demonstrated finding. The corpus is dominated by a limited set of national contexts and cultural variation in achievement values, collectivism and institutional trust may alter the strength of both pathways, so comparative multi-site work across cultural contexts, particularly within the Asian region, is needed to establish the boundary of the model's generalisability. The augmentation–dependence distinction is an idealisation of engagement that is in reality mixed and episodic, which is why the two modes are specified as continuous dimensions. Publication incentives favour both novel benefits and alarming harms, so the observed symmetry may partly reflect dual publication bias and the technology is a moving target, although the model's mechanisms are formulated at the level of psychological function precisely so that they survive capability change (1). Finally, the corpus is restricted to English-language publications and self-reported use almost certainly under-represents dependence-mode behaviour, biasing existing estimates toward zero.

Conclusion

Generative AI is neither a saviour nor a saboteur of student psychology; it is an amplifier whose direction is set by the mode of engagement. Used as a tutor and thinking partner, it satisfies basic psychological needs, builds self-efficacy and initiates a virtuous cycle of empowerment. Used as a substitute for the student's own cognition, it hollows out mastery, breeds anxiety and procrastination and initiates a vicious cycle of erosion. Because both cycles are self-reinforcing, early habits matter enormously; and because the moderators of pathway choice, namely AI literacy, self-regulated learning skill and institutional guidance, are all teachable and designable, the trajectory of a generation of students remains genuinely within institutional influence.

The Dual-Pathway Model reframes an apparent empirical contradiction as unmeasured moderation and yields eight propositions that are testable at the level of the individual use episode rather than the individual student. Validating instruments for engagement mode, integrity anxiety and skill-atrophy perception and testing the feedback loops with longitudinal and randomised designs, are the immediate priorities; until such work is undertaken, the framework is best understood as a structure for organising enquiry rather than a settled account. Two pathways diverge from one tool and universities, educators and students together decide which one is taken.

Abbreviations

AI: Artificial Intelligence, CLT: Cognitive Load Theory, GenAI: Generative Artificial Intelligence, LLM: Large Language Model, SDT: Self-determination Theory, SRL: Self-regulated Learning.

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Author Contributions

Sofia Elias: Conceptualisation, Literature Search, Literature Screening, Writing - Original Draft, Nurul Aisyah Kamrozzaman: Conceptualisation, Supervision, Theoretical Framework Development, Critical Revision. Both authors screened sources independently at the eligibility stage, resolved

disagreements by discussion and read and approved the final manuscript. Both authors accept full responsibility for the content of the work.

Conflict of Interest

Sofia Elias declares no conflict of interest. Nurul Aisyah Kamrozzaman declares no conflict of interest.

Data Availability

No new data were generated or analysed in this study. All sources synthesised are published works listed in the reference list and are available from their respective publishers.

Declaration of Artificial Intelligence (AI) Assistance

During the preparation of this manuscript, the authors used ChatGPT and Grammarly to assist with language editing, grammar and clarity refinement and formatting alignment with journal guidelines. After using these tools, the authors reviewed and edited the content as required and take full responsibility for the content of the publication. No generative AI tool was used to generate scientific content, data, analysis or conclusions.

Ethics Approval

This study is an integrative review of previously published literature and involved no human or animal participants. Ethical approval was therefore not required.

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