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Education Psychological Challenges and Research Gaps in GenAI-Integrated Creative Disciplines: A Scoping Review

Jiawei Guo
City University of Macau
Yi Dai
yidai@cityu.edu.mo
City University of Macau
Chendi Wang
The Affiliated Hospital of Hubei Provincial Government
Zhixin Zhang
City University of Macau
Keyi Guan
Wuhan City Polytechnic

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Abstract

In creative education, a field encompassing art, design, architecture, and related disciplines focused on originality, authorship, and practice-based work, there is a growing adoption of Generative Artificial Intelligence (GenAI). Unlike conventional educational technologies that primarily support skill acquisition or task execution, GenAI autonomously generates creative content, thereby reshaping students' engagement with ideation, authorship, and creative agency in these learning environments. Following PRISMA-ScR guidelines and an OSF-registered protocol, this scoping review systematically mapped 20 empirical studies identified from Web of Science, Scopus, and IEEE Xplore (2021–2026). Results indicate that GenAI is primarily integrated via visual or multimodal tools within studio-based courses and workshops, with effects varying significantly by disciplinary context and learner experience. While GenAI enhances self-efficacy among novices, it frequently induces career-related anxiety and identity threats among advanced practitioners. Furthermore, current research lacks robust coverage of human–AI collaboration mechanisms, longitudinal developmental trajectories, and unified theoretical frameworks. By synthesizing evidence on applications, psychological impacts, and critical research gaps, this review underscores the necessity for differentiated pedagogies and strengthened institutional frameworks to ensure the responsible integration of GenAI in creative education.

Introduction

In creative education, generative artificial intelligence (GenAI) is transforming how students learn and create by shifting effort from technical execution to ideation and iteration, which enabling professional-grade designs from simple textual prompts instead of complex tool-specific workflows[1,2]. Unlike traditional design software that assists human creators, GenAI systems autonomously generate original content, fundamentally altering the creative process. This technological shift has rapidly transformed creative education, from intensive design workshops to regular studio classes[3].

Traditional educational technology research, focused on usability and cognitive factors, fails to address GenAI's distinctive impact[4]. By shifting students from pure creators to evaluators and curators of AI-generated content, GenAI transforms the fundamental nature of creative agency and professional identity[5,6]. This redefinition raises critical questions about authorship, creative ownership, and skill value that extend beyond conventional tool mastery concerns[7,8].

Existing studies reveal GenAI's paradoxical impact on creative education, presenting both significant opportunities and psychological challenges for learners. On the positive side, GenAI lowers technical barriers by transforming complex creative tasks into natural language interactions, enabling novice students to generate high-quality visual designs and architectural renderings[9]. This accessibility democratizes creative expression and accelerates ideation, particularly benefiting learners with limited prior expertise[10]. Research indicates that students using GenAI as a creative scaffold report enhanced creative self-efficacy and increased engagement during early design stages[11].Conversely, students face

mounting psychological risks from GenAI integration. Many report anxiety about skill obsolescence and career displacement, fearing that their foundational creative competencies may become redundant[12]. The perception that GenAI can produce outputs comparable to human work challenges students' sense of creative authorship and professional identity[8]. Additionally, process-level concerns emerge as students struggle with over-reliance on GenAI suggestions and frustration with unpredictable outputs that misalign with their creative intentions[13]. These contrasting findings establish GenAI as a double-edged tool that simultaneously expanding creative possibilities while introducing new psychological tensions that reshape the creative learning experience[6,7].

Navigating the double-edged nature of GenAI in creative education requires a holistic approach that simultaneously addresses its potential to accelerate ideation and its risks to professional identity. Establishing this balance is critical for developing evidence-based pedagogies that maximize technical benefits while safeguarding student well-being. However, current empirical research remains too fragmented to support such a comprehensive framework. First, the literature predominantly prioritizes tangible design outcomes, such as task efficiency and novelty, over students' psychological well-being[14,15], often neglecting diverse populations beyond undergraduate cohorts[16,17]. Second, theoretical and methodological inconsistencies hinder cross-study comparison. Researchers employ disparate theoretical lenses, such as Self-Determination Theory[18] and Social Cognitive Theory[19], or focus narrowly on technology acceptance[20], without integrating these cognitive and emotional dimensions. Furthermore, measurement approaches vary widely, ranging from qualitative anecdotal reflections[21] to unstandardized psychological scales[22], making direct synthesis difficult. Third, critical modulators of the creative experience remain underexplored, particularly individual learner differences like personality traits[23], cross-cultural variations in adoption[24], and emerging ethical anxieties regarding authorship and intellectual property[25,26]. Consequently, the field currently lacks a systematic mapping of the interdependent cognitive and identity-related pathways that determine whether GenAI serves as a creative scaffold or a threat to student agency.

To address these gaps, this paper presents a scoping review of empirical studies across art, design, and engineering education that systematically maps GenAI implementation from undergraduate settings to professional practice. Specifically, the review aims to document associated psychological impacts, which range from cognitive shifts to identity-related anxieties, and to critically examine the theoretical fragmentation that hinders current research. Guided by a structured coding framework (Appendix A), our analysis synthesizes these disparate findings to propose a new conceptual framework (as shown in the Fig. 1). This framework illustrates how cognitive, emotional, and identity factors intertwine to produce dual-edged outcomes. Through this analysis, the review seeks to equip stakeholders with the evidence-based roadmap needed to ensure students develop both technical proficiency and psychological resilience in the GenAI era.

Research question

What is the current state of research on the psychological impacts of GenAI in creative education, and how have these impacts been explored and categorized? We aimed to explore the following themes:

(RQ1) How is GenAI implemented in creative educational contexts?

(RQ2) What psychological challenges arise from students' use of GenAI?

(RQ3) What is the gap for future work?

Methods

A scoping review approach was adopted to achieve the study's core objectives, including examining the extent of research activity on GenAI in creative education, determining the value of a full systematic review, summarising and disseminating key research findings, and identifying gaps in existing literature. Guided by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) guidelines to ensure rigorous reporting, our a priori protocol is registered with the Open Science Framework (OSF). Aligned with the aforementioned research questions, we systematically discovered, profiled, and Identified. empirical studies related to GenAI's application in creative education over the past five years (2021–2026). Given that mainstream GenAI tools for creative practice, such as DALL-E, were first launched in 2021, relevant research on their educational integration has only emerged and accumulated in recent years, which making this five-year time span scientifically justified, as it fully covers the key period of GenAI's penetration into creative education and ensures the timeliness and relevance of the included literature. We adopted two steps to examine these studies: systematic selection of papers through database searches and hand-screening (in line with the PRISMA-ScR framework), and coding of the selected papers using the pre-established structured coding scheme detailed in the Appendix A.

Paper selection

To guarantee the quality of selected studies, our research team reviewed well-recognized peer-reviewed articles in the Web of Science (WOS) core collection, Scopus, and IEEE Xplore. We sourced studies through two complementary channels. First via database searches. To ensure the credibility and relevance of our literature pool, we focused on peer-reviewed work from three high-impact academic databases (Web of Science Core Collection, Scopus, IEEE Xplore), with the following database-specific search strings. The specific search strings tailored to each database are detailed in the Appendix B.

The inconsistent inclusion of psychological keywords alone across the three databases stems from three key factors: Scopus's stronger coverage of humanities and social science research allows it to capture studies on students' psychological responses to AI without excessive noise; Web of Science Core Collection, by contrast, prioritizes the core link between AI tools and art/design education, while IEEE Xplore focuses on technical and user-perception studies. Adding psychological keywords to the latter two databases would likely introduce irrelevant literature, so they were omitted there.

In the “Identification of studies via other methods” stage (as shown in the Fig. 2), we conducted backward reference checking: we reviewed the reference lists of relevant studies retrieved from database searches, to identify additional eligible literature that aligned with our focus on GenAI’s psychological impacts on creative education students.

These databases contain reputable journals with recognized impact factors. The articles retrieved in WOS and Scopus can be further refined into social science or educational categories, allowing for more precise retrieval. Additionally, given the focusof this research on the use of technology in education, the IEEE database provides focused research in scientifc and technical disciplines.

During full-text screening, we applied pre-defined exclusion criteria and inclusion criteria to ensure alignment with the research focus:

Exclusion criteria

Studies were excluded in case they simply talked about the technical capabilities of GenAI or the way it has been applied pedagogically but did not address the psychological reactions of students; focused on perceived usefulness or ease of use without negative emotions, such as anxiety or threat; or applied GenAI to non-creative situations, including ChatGPT to debug a piece of code or summarize text.

Inclusion criteria

The studies included in this study had to investigate student psychological responses, including perceptions, attitudes, emotions (e.g., anxiety or threat), satisfaction, and behavioral intentions; involved art or design students utilizing GenAI tools to participate in creative activities, and reflection of the experiences; applied psychological or technology acceptance theories to investigate problems in creative education; and used qualitative, quantitative, or mixed empirical research.

Coding procedure

The selected articles were systematically coded to enable a structured synthesis aligned with the three research questions. A multi-layered coding framework was developed to capture both the contextual implementation of GenAI and its psychological dimensions.

To address RQ1 (how GenAI is applied), each study was coded according to its primary exposure context: Workshop, Studio/Course Task, Challenge/Hackathon, Controlled Experiment, Survey-only, or Naturalistic Use. This categorization clarified the pedagogical modes through which GenAI tools were introduced and utilized in creative education.

For RQ2 (psychological challenges), we extracted and coded data concerning learners’ self-efficacy, identity threat, and forms of anxiety (creativity, employment, and ethics-related). The presence, direction (e.g., enhanced or reduced), and reported intensity of these psychological constructs were documented based on explicit findings or discursive mentions in the texts.

Regarding RQ3 (research gaps), we analyzed the “limitations” and “future work” sections of each paper. Recurring recommendations were grouped into ten thematic gaps (C1–C10), allowing a systematic identification of under explored areas.

To ensure reliability, the coding was first performed by the lead author. A second researcher then independently coded a subset (20%) of the articles. Any discrepancies were resolved through discussion until consensus was reached. The coded data were analyzed both quantitatively (frequencies, percentages) and qualitatively (thematic patterns), with findings presented in the subsequent sections.

Results and discussion

In accordance with the content analysis and coding criteria examined. The mentioned above 20 papers were thoroughly following sections present the results and provide a corresponding discussion of the research questions.

RQ1: What Are Hypothetical GenAI Applications in creative Education?

This scoping review is a synthesis of 20 empirical studies (3,952 participants) to investigate the application of GenAI in creative training and offers insight into geographic settings, study area, and the level of experience learners have with it. To provide an overview of the empirical landscape of the included studies before examining specific application patterns, Fig. 3 summarizes the distribution of studies across geographic regions, disciplines, GenAI tool types, and participant groups.

Distribution of GenAI Tools in Creative Applications

Table 1 demonstrated that GenAI applications mostly revolve around visual generation and mixed workflows. Three studies (30%) are dedicated to text-to-image models only, like Midjourney, DALL-E, or Stable Diffusion, whereas seven (35) of them merge the text-to-image with text-based AI (e.g., ChatGPT) to perform creative tasks altogether. Five percent (1) adopt only large language models to do text-based work, and six (30) do not specify tools or leave them to choose freely 27–29, though some report the tools students ultimately selected.

Item	Option	Frequency	Percentage(%)
GAI Tool	LLM Text-based	1	5
	Visual Generation-based	6	30
	Mixed	7	35
	Unclear	6	30
Exposure Main	workshop	5	25
	Studio	6	30
	Challenge/Hackathon	1	5
	Controlled task	3	15
	Survey-only	2	10
	Naturalistic use	3	15
Geographic Stratification	East Asia	10	50
	West & Australia	6	30
	Others	4	20
Disciplinary Categorization	Visual/Spatial Design	9	45
	Pure Arts	2	10
	Mixed/Interdisciplinary	8	40
	Others	1	5
Student Type	Undergraduate	14	70
	Graduate/Professional/Mixed	6	30
Research Design Type	Qualitative	4	20
	Quantitative	6	30
	Mixed-Methods	6	30
	Others	4	20
Total		20	100

Table 1. Summary of Application Contexts and Intervention Models of GenAI in Creative Education

Integration Methods

The major ways in which GenAI can be incorporated in education arise in six ways. Studio-based coursework (6 studies, 30%), in which GenAI tools are integrated into existing design modules or semester-long projects instead of standalone exercises, is the most prevalent. This practice makes GenAI the logical follow-up to the design practice but creates the risk of commodifying creativity in case of a lack of critical reflection[30]. Teaching prompt engineering and design basics can also be used as a structured scaffold to learn more about the traditional and GenAI-mediated creative activities[27,31].

One in 4 studies (25%) utilized workshop-style interventions, which are intensive 2–4 week workshops that address a particular problem like sustainable product design or interface development[28]. These interventions provide opportunities for experimenting with new tools in supportive learning environments without the stress of immediate grading. However, post-training statistics on long-term skill transfer remain scarce, with recent crossover studies showing mixed results on the persistence of GenAI-supported ideation skills[32]. The experimental tasks are controlled (3 studies, 15%), which permits

comparison of GenAI-assisted workflow and traditional workflow to draw causal conclusions, but highly structured tasks might not represent practice. Self-directed GenAI usage is also reflected in naturalistic observations (15, 3 studies), where the authors report the processes of students acquiring their workflows and preferences regarding the tools[31]. Two of the studies (10%), however, utilise surveys only to measure attitude toward GenAI with no actual tool use[23], and one study (5%) reports a 72-hour advertising competition at high pressure, simulating the conditions of a professional environment[27].

Geographic Characteristics, Disciplinary Characteristics, and Participant Characteristics

Fifty (50%) of the studies are based in East Asia (10 studies, 50%), six (30%) are based in the Western countries and cross-regional (Australia), and four (20%) are based in other regions or cross-regional collaborations. Visual and spatial design disciplines (industrial design, architecture, graphic design) represent 45% of the studies, mixed/interdisciplinary situations 40% and pure arts 10%, with one study (5%) considering general creative cognition. The majority of the participants are undergraduates (14 studies, 70%), and the rest contain graduate students, early-career professionals, or mixed samples. In terms of methodology, there is a balanced spread of studies in terms of quantitative (6, 30%) and mixed-methods (6, 30%) designs, four qualitative (20) and four exploratory/conceptual designs (20)[27,28].

Patterns of Use Disciplines

The application of GenAI differs radically depending on the field. Text-to-image tools used in spatial visualisation, image exploration, and quick prototyping are also predominantly used by architecture and industrial design students, and they can assist in breaking the limitations of technical drawing but could circumvent the cognitive processing of buildability or material constraints[28,31]. The graphic design and advertising students are likely to work with multi-tool flows, which will involve image generators with ChatGPT to write a copy or a mood board, balancing efficiency with the task of preserving creative coherence[27,30]. Students of fine arts are more sceptical about the application of GenAI, as they are concerned with authenticity and authorship[23], and UX design students are more open to GenAI because of its storyboarding and communication capabilities, instead of personal expression[9,33].

Learner Experience

Engagement is influenced by experience: the undergraduate learners with limited experience may employ GenAI as a scaffold to visualise something that cannot be done with their hands, a process known as the democratisation of creativity[28,30], but may inevitably become over-reliant at the expense of developing their skills[23,27]. GenAI is also utilised by advanced students and early-career professionals to create more efficiency, e.g., by automating any repetitive procedure, like creating colour palettes or layout variations, to devote more attention to higher-level concept development. In spite of this efficiency, they

note anxiety related to skill obsolescence and the possibility of expertise undermining, as novices will be able to produce similar results with the help of GenAI[30,31].

RQ2: What Psychological Challenges Do Students Face When Using Generative GenAI?

Based on the analysis of 20 empirical studies, this section synthesizes the core psychological challenges faced by creative education students in GenAI use and discusses their key implications for practice, focusing on summarizing research patterns.

Table 2
Frequency and Proportion of Psychological Challenges Associated with Student Use of Generative AI in Included Studies (N = 20)

Item	Option	Frequency	Percentage(%)
Identity Threat Presence (numeric)	No identity threat	8	40
	Indirectly mentioned	4	20
	Explicitly reported	8	40
Self-Efficacy Presence (numeric)	Not measured/mentioned	3	15
	Indirect/implicit	7	35
	Explicitly measured	10	50
Self-Efficacy Direction (numeric)	Not applicable/measured	4	20
	Reduced/negative	1	5
	Mixed/both	8	40
	Enhanced/positive	7	35
Self-Efficacy Severity (numeric)	Not applicable	4	20
	Moderate	13	65
	High/Significant	3	15
Career Anxiety(0–1)	No	13	65
	Yes	7	35
Creativity Anxiety(0–1)	No	14	70
	Yes	6	30
Ethical Anxiety(0–1)	No	17	85
	Yes	3	15
Presence of Anxiety(numeric)	None	8	40
	Indirectly Mentioned	1	5
	Explicitly Mentioned	11	55
Total		20	100

The results of the review (see Table 2) indicate that the core psychological challenges identified are concentrated in three interrelated areas, with clear distribution patterns across studies. First, anxiety is a notable response, explicitly reported in 55% of studies and indirectly mentioned in 5%. Among subtypes, career anxiety (35% of studies) and creativity anxiety (30% of studies) are the main concerns, focusing

on GenAI's potential impact on creative skills' value and original expression, while ethical anxiety is less common (15%) and primarily linked to ambiguous use guidelines. This pattern indicates that students' anxiety centers on core creative and professional values rather than widespread ethical resistance.

Second, identity threat is a core challenge, mentioned in 60% of studies (40% explicitly reported), revolving around the reconstruction of "creative practitioner" identity when GenAI can generate creative outputs independently. Experience level is a key differentiator: senior students and early-career professionals are more vulnerable to such threats due to their investment in traditional skills, while novices tend to view GenAI as an enabler of emerging creative identities[32]. This difference suggests that psychological responses to GenAI are not universal but context-dependent.

Third, self-efficacy, measured in half of the reviewed studies, displays a conditional pattern. Enhanced self-efficacy is reported in 35% of studies, particularly among novices benefiting from skill compensation, while 40% reveal mixed effects among more experienced users who weigh efficiency against skill deterioration. Only 5% indicate reduced self-efficacy. Most effects are of moderate intensity (65%), illustrating the inherently fragile perception of competence in GenAI use.

Synthesizing these findings, GenAI-induced psychological challenges are structured around identity threat, conditional self-efficacy fluctuations, and domain-specific anxiety. Building on this synthesis, self-efficacy and anxiety appear not merely as parallel outcomes, but as interrelated psychological mechanisms through which GenAI use shapes students' creative engagement and identity stability.

For practice, the key implication is differentiated pedagogy aligned with experience level: novices benefit from complementary integration of GenAI and foundational training to leverage self-efficacy gains without dependence[9]; seniors need support for identity reconstruction, emphasizing GenAI-irreplicable human capacities[13,34]. Furthermore, both GenAI proficiency, found to correlate with decreased anxiety in roughly 15% of studies, and clear usage guidelines represent important protective factors, suggesting that AI literacy should be systematically incorporated into education.

RQ3: What is the gap for future work?

Our analysis of future research recommend across 20 studies reveals a field grappling with fundamental questions about how generative GenAI should be integrated into design pedagogy. To provide a structured overview of these unresolved issues before detailing their frequencies in Table 3, Fig. 4 maps the landscape of research gaps in GenAI-assisted creative education. While existing research has documented various applications of GenAI tools in educational settings, the gap statements authors articulate point to deeper epistemological and methodological challenges that remain largely unresolved[35].

Table 3
Results of the Secondary Coding Frequency Distribution for Future Research Gap Themes (C1–C10)

Item	Option	Frequency	Percentage(%)
C1	0.0	15	75
	1.0	5	25
C2	0.0	16	80
	1.0	4	20
C3	0.0	17	85
	1.0	3	15
C4	0.0	16	80
	1.0	4	20
C5	0.0	16	80
	1.0	4	20
C6	0.0	14	70
	1.0	6	30
C7	0.0	15	75
	1.0	5	25
C8	0.0	17	85
	1.0	3	15
C9	0.0	14	70
	1.0	6	30
C10	0.0	16	80
	1.0	4	20
Total		20	100

Dominant Gap Themes

The most remarkable result is the eminence of two intertwined issues. Six out of 20 studies explicitly state the need of research into human-AI collaboration mechanisms, whereas as many of them focus on the need to conduct longitudinal and causal research designs (as shown in the Table 3). These priorities cannot be seen as accidental: they directly respond to the recognized gap between rapid GenAI adoption and the unclear efficacy of such tools for sustained learning[36–38]. The sphere has already left behind the

question of whether students use GenAI tools, but there is still no basic insight into how such interactions evolve over time and which patterns of engagement can be used to generate meaningful learning outcomes[39,40]. The investigators point to a black box issue in collaboration between human beings and GenAI. Student prompts, design briefs (inputs), AI-generated pictures, refined concepts (outputs) are visible, whereas the process between is a black box. Questions of the essence are: at what point do students use AI, and at what point do they work on their own? What is the process of GenAI suggestions evaluation and integration? What is the situation when the outputs of GenAI contradict the original design goals? These are the main questions that can be discussed in connection with GenAI-enhanced design learning.The equally frequent calls for longitudinal research reflect a related frustration with the field's current methodological constraints[41].

Research Needs in the Long Run

The demand of longitudinal research is a manifestation of the frustration with methodological limitations[41]. A majority of the researches focus on snapshots: workshops, semester-based courses, or single projects[42]. However, design learning is cumulative: skills build up, aesthetic sensibilities become more exalted and students internalize professional judgment with time. We cannot longitudinally follow a group of courses or stages of early career and track how exposure to GenAI at an early age scaffolds or retards this developmental pattern[43]. Most existing studies capture snapshots: a semester-long course, a single project, sometimes just a workshop or brief intervention[39]. But learning design is inherently developmental. Skills build cumulatively, aesthetic sensibilities develop over time, and students gradually internalize professional judgment. Without tracking learners over extended periods, ideally across multiple courses or even into the early stages of their careers, we cannot determine whether early exposure to GenAI supports or hinders this developmental trajectory[43].

Additional Gaps

Five articles list the gap areas concerning discipline-specific evidence and influences of creative processes (as shown in the Table 3). Systems based on GenAI might fail to identify specific needs of a specific design project, such as industrial design material limitations, cultural sensitivity in graphic design, or regulatory context in architecture[44]. Fears of homogenising the creative process are indicative of a fear that AI-generated work at an adequate level of technical skill dilutes the experimental, risk-taking actions that are necessary in a true design innovation[45].

The gaps in the experience levels of the learners, GenAI literacy development, attitudinal factors, and generalisability (four studies each) were found to be moderate. Themes of lower frequencies, such as the strategies of pedagogical integration and ethical governance, are only found in three studies. This can be a sign of new awareness or lack of problematisation in the present discourse[46].

Gap Sensitivity to Context

We compared the exposure types in the students and the gaps reported using Kendall t (as shown in the Table 4). The vast majority of the gaps are independent of context, whereas others are highly sensitive. The issues of ethics and governance, such as the one of students, where the outcome of their GenAI work has a real-world impact (τ = 0.33), can be seen as illustrations of the influence of the stakes on the attention of the researchers. Gaps on the levels of learner experience, on the other hand, are associated with adverse exposure context (τ = -0.33), which implies that low-level courses provoked the concern about the risks of the development, whereas high-level courses presuppose self-regulation. A moderate positive correlation (τ = 0.22) between pedagogical integration and long-term needs (τ = 0.20) demonstrates that long-term instructional environments manifest systematic integration and long-term impact issues.Conversely, gaps around learner experience levels showed a negative correlation with exposure context (τ = −0.33).

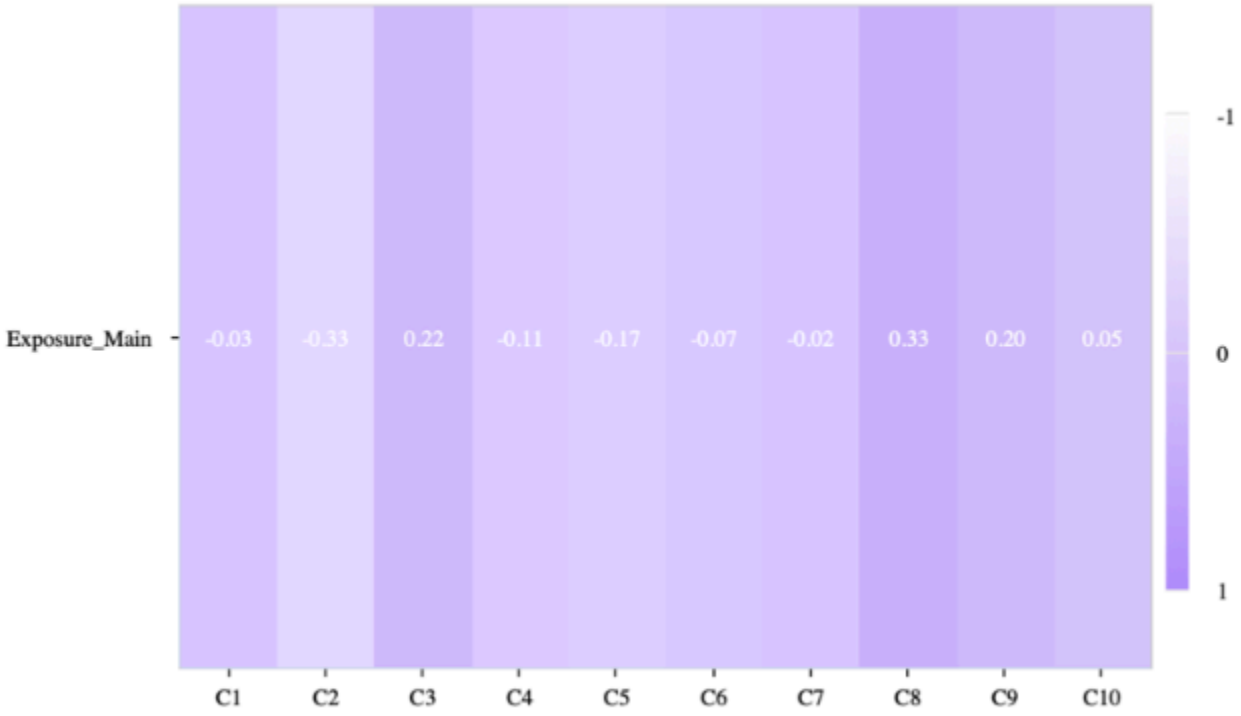


Table 4 Kendall's τ correlations between exposure context and research gaps (C1–C10).

Studies focusing on introductory or foundational courses were significantly more likely to emphasize the need for stage-differentiated research. This pattern suggests that when researchers observe novice students engaging with GenAI tools, they become alert to potential developmental risks. For example, early over-reliance on GenAI could bypass the iterative struggle that is essential for developing design judgment. In contrast, these concerns tend to diminish in advanced learning contexts, possibly because researchers assume that more experienced learners are better able to regulate their use of GenAI independently.

Moderate positive associations for pedagogical integration (τ = 0.22) and longitudinal design needs (τ = 0.20) suggest the presence of a distinct contextual dynamic444. Specifically, studies conducted within

formal and sustained instructional environments, which include full-semester courses rather than short-term workshops and integrated curricula instead of isolated experiments, more frequently identified these specific gaps. This finding can be explained by the fact that the implementation of pedagogical models at scale over extended periods necessitates addressing systematic integration and long-term impact6. Such complex factors may not be observed during interventions of shorter duration.

Possibilities of Future Research in GenAI-Assisted Creative Education

The prominence of collaboration mechanism and longitudinal design gaps suggests the field needs a shift in research infrastructure. We need studies that can capture temporal dynamics and process-level detail simultaneously. Such studies should employ mixed-methods designs, which involve following student cohorts while collecting rich interaction data[47]. This isn't just about "better" research in some abstract sense; it's about matching our methods to the phenomena we're trying to understand[48]. Learning with GenAI unfolds over time through repeated interactions, so our research designs need to accommodate that temporal and interactive structure[49].

Second, the contextual sensitivity of certain gaps, which is particularly pronounced in areas such as learner stages and ethical concerns, argues against one-size-fits-all research or policy approaches. Novice-focused research should perhaps prioritize questions about scaffolding and skill development, while studies in advanced or professional contexts might usefully foreground ethical frameworks and governance structures[29]. This doesn't mean abandoning general principles, but it does suggest we need differentiated research strategies that acknowledge different stakeholder concerns across educational contexts[50].

Third, Several major gaps, such as discipline specificity, GenAI literacy, collaboration mechanisms, creative impact, suggests these represent fundamental challenges requiring coordinated, sustained research effort. No single study will resolve them. The field might benefit from more collaborative initiatives: shared measurement instruments, pooled datasets, multi-site replications that can build cumulative knowledge rather than isolated case studies[51,52].

Of course, this analysis has clear limitations. Twenty studies constitute a modest sample, and our binary coding of gap presence necessarily simplifies what researchers actually wrote, losing nuances in how extensively different studies addressed various concerns[53]. Some studies discussed certain gaps extensively while others mentioned them in passing, but our coding treats these equivalently, potentially obscuring important variations in depth of engagement. The exposure context variable itself is a rough proxy for what are surely more nuanced instructional situations. Moreover, it is crucial to recognize that correlation, even when statistically suggestive, does not establish causation[54]. While we can observe that ethical gaps appear more frequently in certain contexts, this observation alone cannot demonstrate that the context itself produces the awareness; it remains possible that other factors, such as researcher backgrounds or publication venues, are driving the pattern[55,56].

Nonetheless, these findings provide a systematic examination of the field's developmental trajectory. The research gaps identified are not merely wish lists; they reflect genuine uncertainties and unresolved tensions in current practice[57]. The consistency of certain core concerns, which include human-AI collaboration mechanisms and longitudinal impact, across diverse studies underscores that these are not idiosyncratic preferences but a shared recognition of fundamental knowledge deficits[8]. Meanwhile, the contextual variation in other gaps reminds us that research priorities need not be uniform to be valid, as different educational contexts may legitimately give rise to distinct research questions[58].

Perhaps most importantly, this analysis reveals that the field is asking increasingly sophisticated questions. Early AI-in-education research often focused on proving feasibility or documenting adoption[59]. The gaps identified here aim higher: understanding mechanisms, establishing causality, differentiating contexts, addressing ethics. That shift from "does it work?" to "how, when, for whom, and at what cost?" marks progress toward a mature research paradigm[60,61]. The gaps we've identified aren't deficiencies so much as invitations. A collective articulation of what the field needs to know next[57].

Conclusion

This scoping review synthesises existing empirical literature on the application of GenAI in creative education, covering disciplines such as art, design, and engineering, with a particular emphasis on students' multidimensional psychological impacts. The review has explored the different forms of GenAI integration such as studio work, workshop, hackathon and naturalistic application. These applications were compared in varying geographic settings and in various groups of learners such as undergraduate, graduate, and novice professionals.It also mapped core psychological outcomes, such as anxiety related to career, creativity, and ethics, identity threats, and fluctuations in self-efficacy.

Furthermore, the review recommends differentiated pedagogical approaches tailored to learners' experience levels. These include leveraging the complementarity of GenAI and foundational training for novice learners to prevent excessive reliance on automated tools, guiding advanced learners to rebuild their professional identity so that they can overcome fears of skill redundancy and uphold their professional competence, and delivering systematic AI literacy instruction to foster critical awareness of the technology's potential threats.While the dual-edged nature of GenAI's impacts, such as enhancing efficiency and ideation while posing psychological challenges, is well-documented, the study also identified significant limitations in current research. These constraints can be grouped into three broad categories: scope, theory and methods. With regards to scope, also significant subgroups like students of fine arts and several of its subfields are underrepresented, and at the theoretical and methodological stages, the research is divided between different frameworks and covers fewer of the fundamental topics, such as cross-cultural differences and the ethical management of AI-supported creativity.

Creative education stakeholders face unique challenges related to GenAI's disruption of traditional creative identities and skill valuation. This disruption necessitates the adaptation of generic technology education frameworks such as echnology Acceptance Model and GenAI-TAM to address the nuanced

needs of creative disciplines. Future research should prioritise the development of integrated theoretical models to explain the interactions between cognitive, emotional, and identity-based impacts. Additionally, it is essential to employ rigorous longitudinal and causal research designs to capture long-term learning trajectories. There is also a need for comprehensive, discipline-specific assessments of GenAI's influence on creative processes, particularly in relation to its potential for homogenisation and skill erosion.

Systemic changes within educational institutions, such as the establishment of clear GenAI use guidelines, the integration of AI ethics and authorship education into curricula, and the promotion of human-AI collaboration mechanisms, could play a crucial role in addressing psychological risks effectively. The review underscores the potential for a combination of individualised support, pedagogical innovation, and institutional strategy to leverage the benefits of GenAI while nurturing students' psychological resilience and preserving the core values of creative practice in the AI era.

Declarations

Author Contribution

Conceptualization, Yi Dai and Jiawei Guo.; methodology, Yi Dai , Jiawei Guo.; software, Jiawei Guo writing—original draft preparation, Jiawei Guo and Yi Dai; validation, Jiawei Guo and ZhangZhi Xin.; writing—review and editing, Yi Dai and Jiawei Guo.; supervision, Chendi Wang and Keyi Guan.; funding acquisition, Yi Dai. All authors have read and agreed to the published version of the manuscript.

Data Availability

The data that support the findings of this study are available from the corresponding author upon request.

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Figures

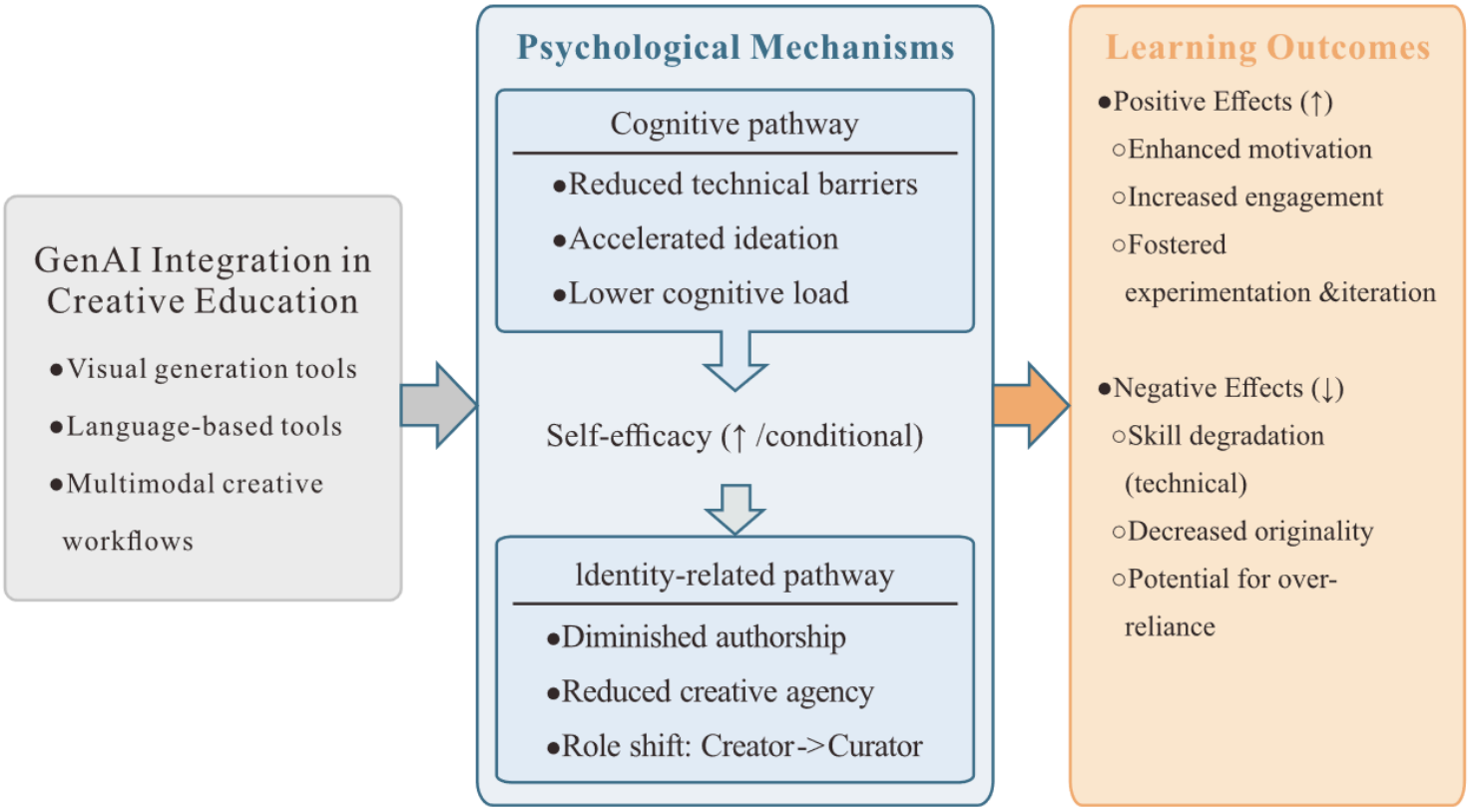


Figure 1

Conceptual framework of the dual-edged psychological mechanisms of GenAI integration in creative education

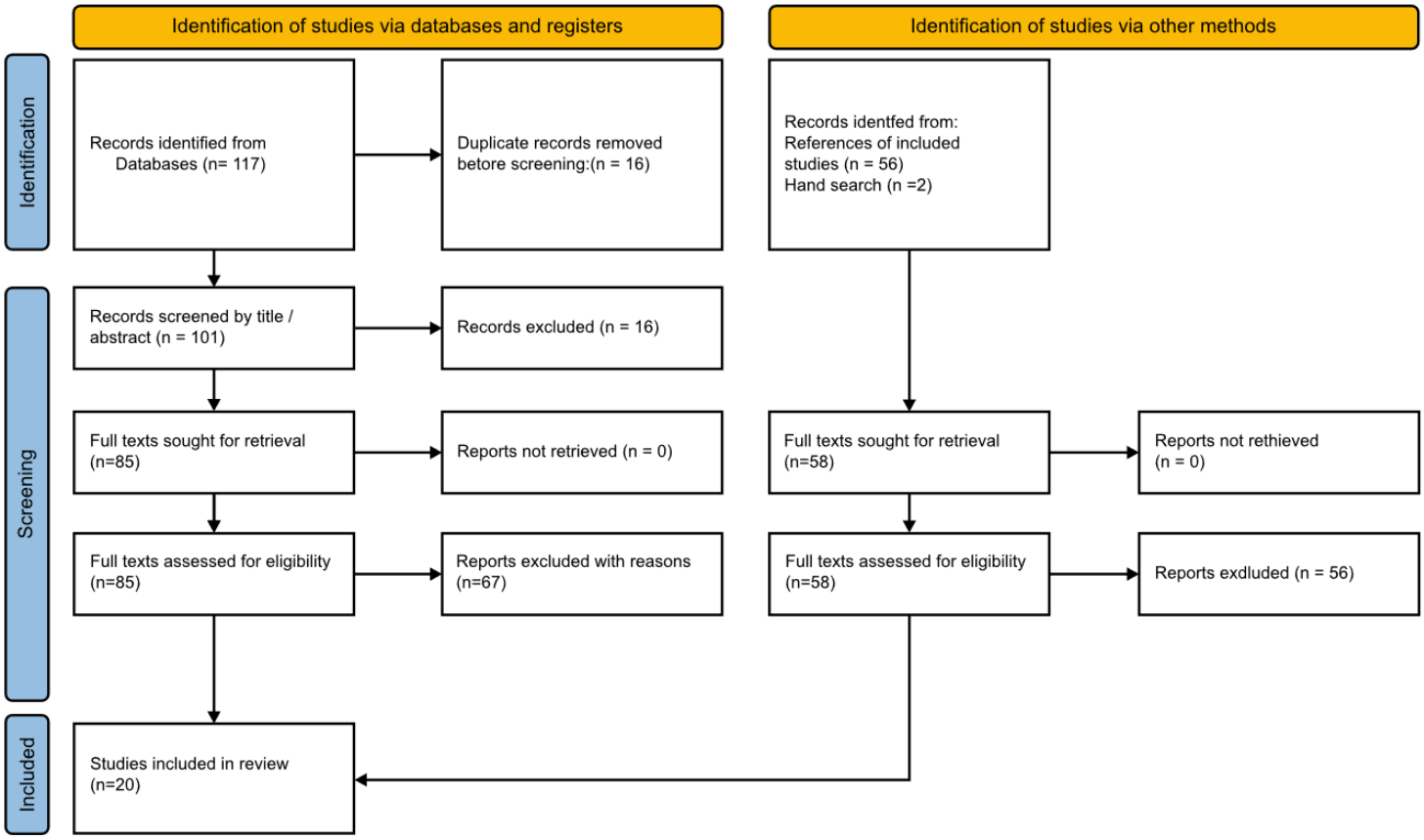


Figure 2

Study flow diagram for the scoping review process

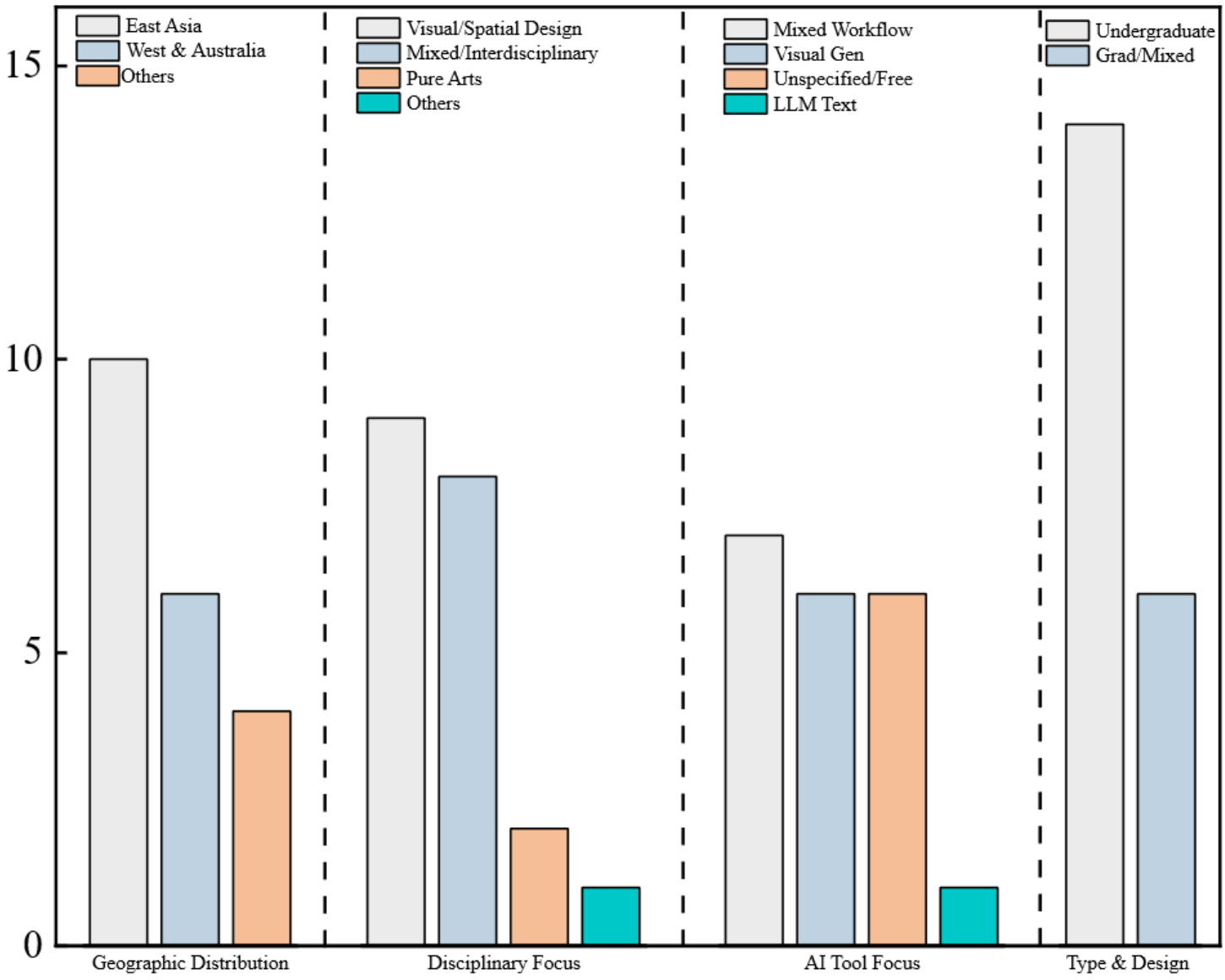


Figure 3

Landscape of the included empirical studies (N = 20)

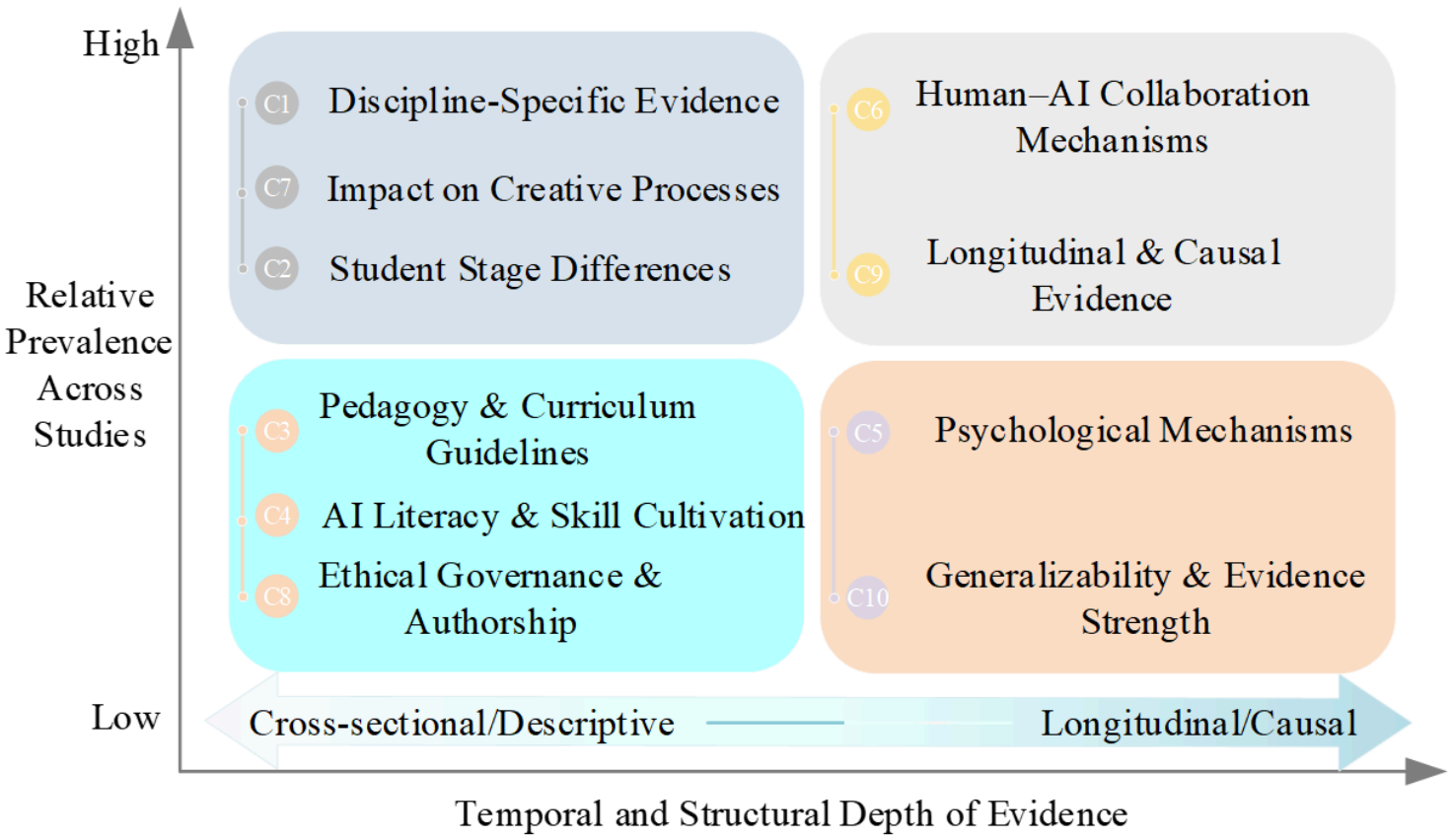


Figure 4

Landscape of research gaps in studies on GenAI-related psychological challenges in creative education

Supplementary Files

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