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Evolving methodological trends in generative AI research for design and education: A Systematic review and future directions

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Abstract
Generative AI (GenAI) is rapidly reshaping studio- and project-based learning within design disciplines, yet its methodological foundations remain uneven. This systematic review examines how research methods have evolved at the intersection of GenAI, design, and education. Following PRISMA 2020 procedures, major databases were searched for studies published between 2020 and 2025. From 100 records identified, 61 peer-reviewed studies were retained for double-coded analysis across research design, instruments, analytical techniques, tool–task alignment, educational contexts, and markers of rigor. The corpus is dominated by secondary syntheses, with systematic and bibliometric reviews comprising 41.0% of studies, while empirical research remains less common (quantitative: 19.7%; qualitative: 13.1%; mixed methods: 4.9%). A sharp acceleration in publications has occurred since 2023. Although 16 studies reported efficiency gains—such as reductions of approximately 40–55% in visualization turnaround time and 1.5–2 times more design iterations—the generalizability of these findings is constrained by reliance on small-scale, single-site pilots. Methodological transparency and rigor are recurring weaknesses: 68.9% of studies describe analytical procedures only in generic terms, 39.3% omit survey or observation instruments, 60.7% fail to specify AI tool versions or prompting strategies, and virtually none report preregistration or replication. Inter-coder reliability was documented in only 3.3% of cases. In addition, outcome measures remain heterogeneous and rarely standardized across process-level indicators (e.g., prompt–response trajectories, density of peer critique) and product-level metrics (e.g., expert-rated creativity with reliability checks).On this basis, the review proposes a forward-looking agenda: (i) enforce transparent reporting using standards such as PRISMA and TOP; (ii) expand the use of quasi-experimental and mixed-methods designs with longitudinal, multi-institutional samples; (iii) establish standardized measurement frameworks that integrate process and product indicators; (iv) align tools with tasks, for instance applying language models to critique and text-to-image systems to ideation, supported by explicit scaffolds; and (v) embed ethics-by-design and open science practices, including prompt logs, datasets, and rubrics, to enable reproducible and equitable scholarship. Taken together, this roadmap positions GenAI not merely as a technical accelerator but as a methodologically robust and socially responsible catalyst for advancing design pedagogy.

Keywords: Generative artificial intelligence, design education, project-based learning, research methodologies, systematic review, qualitative and quantitative methods, educational technology

Introduction

Generative Artificial Intelligence (GenAI) is rapidly transforming higher education, reshaping perspectives on knowledge creation, expression, and communication. Unlike earlier AI applications, which were largely centered on automation and data-driven analytics, this new generation of AI tools—such as ChatGPT, Midjourney, and Stable Diffusion—can produce original text, imagery, and visual concepts, significantly enhancing human creative potential (Qadir, 2023 [33]; Zawacki-Richter *et al*., 2019) [44].

This shift is especially evident in art and design education, where disciplines like environmental art, landscape architecture, and interior design are experiencing a profound impact from GenAI on teaching and learning. For instance, tools like ChatGPT are employed to craft critical analyses, site evaluation narratives, and reflective essays. Midjourney excels in supporting visual ideation and conceptual sketches, while Stable Diffusion facilitates high-quality visualizations and spatial renderings for final project presentations (Casakin & Wodehouse, 2021 [6]; Torres Carceller, 2023) [39].

Generative AI is beginning to change how design students move from early ideas into visual outcomes. Instead of the traditional step-by-step path, these tools allow a more immediate shift from text or abstract thought into spatial and graphic form. In practice, this often shortens the distance between imagining and testing, making it easier to try multiple options in less time (Ali *et al*., 2024; UNESCO, 2023) [40]. A few authors even suggest that the role of these tools is no longer only technical. They can operate almost like a partner in the thinking process, prompting learners to reflect on choices while also offering unexpected directions. If this argument is accepted, then long-held assumptions about how design education is structured—and how progress is assessed—will require reconsideration.

The research record is not uniform. Several studies emphasize creativity: students are able to produce ideas or combine modes of expression that would be difficult without technological support (Evangelidis *et al*., 2024 [11]; Samaniego *et al*., 2024) [36]. Other accounts stress personalization. Here, AI-driven platforms provide tailored advice and materials, and some reports show higher engagement and achievement when such systems are used (Lin *et al*., 2023; Mulaudzi & Hamilton, 2025). Recent developments in adaptive feedback mechanisms reinforce this point by offering targeted prompts at critical stages of the learning process (Chen & Hu, 2023) [7].

Practical accounts from project-based and studio courses add another dimension. Routine work—drafting, early prototyping, collecting visual references—can be automated, freeing students to spend more time on critique and revision (Samaniego *et al*., 2024 [36]; Evangelidis *et al*., 2024) [11]. Quantitative findings are limited but not absent. Out of 61 studies reviewed, 13 employed measurable indicators. Their results show time reductions of around 30–60% during visualization stages. Several also noted that iteration cycles increased, meaning more versions were attempted within the same teaching period. Although these results cannot be taken as conclusive, they point to a clear tendency: generative AI reduces repetitive labor and extends the opportunity for deeper conceptual engagement.

Although the magnitude of effects varies by task and context, several studies report notable reductions in the time required to progress from initial ideas to visual concepts, alongside increases in the number of design iterations achievable within a single studio session. These outcomes are particularly evident when image-generation tools such as Midjourney and Stable Diffusion are combined with large language model–based drafting and critique. Within the reviewed corpus of 61 studies, 16 (26.2%) explicitly documented measurable efficiency gains. Of these, five reported reductions of approximately 40–55% in turnaround time, while seven indicated that students were able to complete between 1.5 and 2 times more design iterations within the same instructional period. Importantly, such gains depend on appropriate pedagogical scaffolding; without it, there is a risk of superficial outputs and compromised rigor in evaluation (Samaniego *et al*., 2024 [36]; Takona, 2024) [38].

At the same time, concerns remain about the potential consequences of over-reliance on generative AI. As Ifelebuegu *et al*. (2023) and Guan *et al*. (2020) [17] caution, excessive dependence may weaken learners' sense of responsibility and foster superficial engagement with knowledge, leading to a more externalized orientation toward learning. Such tendencies risk undermining the cultivation of critical and reflective capacities in design education.

These concerns intersect with broader debates on academic integrity, authorship attribution, and the responsible use of technology in higher education (Torres Carceller, 2023 [39]; Çela *et al*., 2024) [10]. While ethical and pedagogical discussions have gained increasing prominence, comparatively little research has focused on strengthening the methodological foundations of this emerging field. Without systematic attention to transparency, rigor, and ethics, the potential of generative AI to enhance design pedagogy will remain only partially realized.

There is a great deal of diversity in the field of design research in terms of epistemological orientation and methodological stance. Research is conducted in a variety of ways small qualitative case studies, ethnographies of classroom processes, semi-structured interviews, large sample-size quantitative surveys, quasi-experimental studies and more recently to mixed-methods designs. While controversies persist regarding theories of knowledge, the integrative approaches appear to fulfill the minimum requirements of research. Yet, this diversity has problems, one of which is heterogeneity in methodological quality, difficulty in reproducing studies and non-comparable results. It is hard to know what we have learned, where the gaps are, and how we might begin to think about the future when there is no concerted synthesis of these trends in methods.

Furthermore, little is known about the development of methods used to perform this research. The first studies were mainly of exploratory nature and frequently dealt with sketching possible applications of AI in education. In recent years, the number of empirical works and theoretically ambitious approaches has increased. More recently, systematic reviews, bibliometric studies and mixed methods approaches have emerged to synthesize the growing literature (Mustafa *et al*., 2024 [29]; Zawacki-Richter *et al*., 2019) [44[]. But no study has yet superimposed this map of methodological evolution onto the intersections of GenAI, design and education. This divide makes it difficult for researchers and practitioners alike to assess the current state of the field, which methodologies have been most effective, and where further innovation is needed.

This paper presents a systematic review of methodological developments in generative AI research situated at the intersection of design and education during the period 2020–2025. A structured search across major academic databases initially identified 100 records. Following the PRISMA 2020 framework for screening and eligibility assessment, 61 peer-reviewed studies were retained for full-text analysis and synthesis (Page *et al*., 2021) [31].For the present systematic review, the following three key research questions form the basis:

RQ1: What methodological approaches dominate current research on generative AI in design and education?

RQ2: How have these methodological approaches evolved over time, and what trends can be identified between 2020 and 2025?

RQ3: What methodological gaps and future directions can be identified to advance generative AI research in design and education?

This study makes three key contributions to the literature by addressing critical questions. First, it systematically maps methodological practices, offering scholars, educators, and policymakers a clearer perspective on their strengths and limitations. Second, it identifies evolving trends and the most promising methodologies, shedding light on the future direction of the field. Third, it proposes a forward-looking research agenda that emphasizes methodological boldness, interdisciplinary collaboration, and ethical responsibility as foundational pillars for advancing research at the intersection of generative AI, design, and education.

By doing so, this review builds on prior studies that primarily focused on thematic findings related to generative AI in education. Shifting the emphasis from what has been explored to how research has been conducted, it establishes a foundation for a more rigorous, credible, and ethically grounded knowledge base to guide future educational initiatives.

Materials and Methods

The review followed the PRISMA 2020 framework to maintain clarity in reporting, ensure that each step could be independently traced, and support replication by other researchers (Page *et al*., 2021) [31]. The focus was to identify and analyze methodological developments in studies linking generative AI with design and education during the period 2020–2025, with particular attention to how research designs, data sources, and analytical procedures have evolved.

1. Data Sources and Search Strategy

The database search was carried out between January and March 2025. Four major indexing platforms were selected—Web of Science, Scopus, IEEE Xplore, and Google Scholar—because of their coverage of peer-reviewed studies in technology, education, and design.

The search strings were developed around three clusters of keywords, which were combined through Boolean logic:

- **Technology terms:** “generative AI,” “ChatGPT,” “Midjourney,” “Stable Diffusion,” “large language models,” “AI-assisted design”
- **Education terms:** “education,” “higher education,” “project-based learning,” “pedagogy”
- **Design terms:** “landscape architecture,” “interior design,” “environmental design,” “architectural education”

Examples of the combinations used include “generative AI” AND “design education”. During the process, synonyms and closely related terms were added after an initial scan of the results. To extend coverage beyond the primary databases, forward and backward snowballing was also applied by reviewing the reference lists of relevant papers and identifying articles that cited them. Each decision—whether to retain, exclude, or refine a search term—was documented in order to maintain an auditable record of the search process.

2. Screening and Selection Process

The database searches yielded 100 records for initial consideration. Screening followed a pre-specified four-stage protocol designed to preserve consistency and transparency:

- **De-duplication and consolidation of related outputs:** We normalized titles, authors, and identifiers (e.g., DOI) to remove duplicates. Where multiple publications were drawn on the same empirical dataset, we consolidated them and tracked distinct methodological contributions at the coding stage.
- **Title/abstract relevance screening:** Records were retained only if they substantively addressed generative AI within a design-education context. Purely technical papers lacking an educational setting or methodological detail, and studies unrelated to design or education, were excluded at this step.
- **Full-text eligibility against exclusion criteria:** We excluded (a) non-peer-reviewed items (e.g., editorials, abstracts only), (b) studies without sufficient methodological description or presented solely as conceptual opinion pieces without empirical evidence, and (c) papers misaligned with the design/education focus.

Retraction check: We verified the status of remaining records and removed any article identified as retracted.

Following these steps, 61 peer-reviewed studies m*et al*l criteria and were retained for full-text coding and analysis. The screening trajectory and counts at each stage are summarized in Figure 1 (PRISMA flow diagram). Two reviewers screened records independently; disagreements were resolved through discussion, and all key decisions were documented to maintain a transparent audit trail.

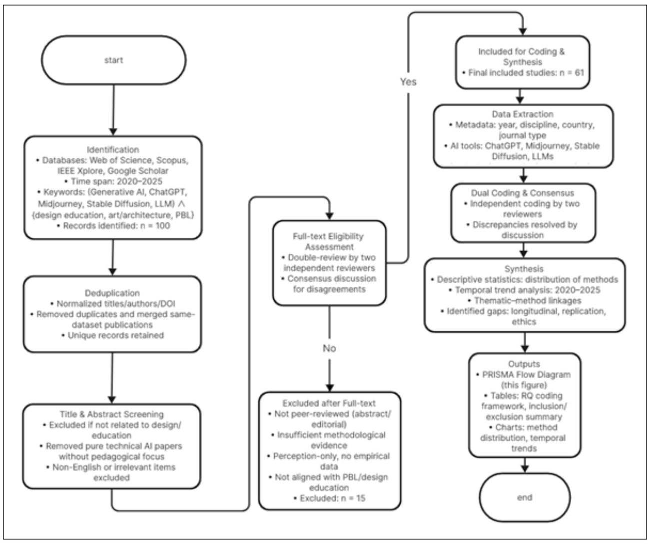

Fig 1: Systematic Review Workflow (PRISMA Flow Diagram)

The processes of identification, screening, eligibility assessment, and inclusion were carried out in full alignment with the PRISMA 2020 guidelines. Figure 1 illustrates the review workflow, beginning with 100 records retrieved from database searches. Of these, 24 were excluded at the title and abstract stage, and a further 15 were excluded following full-text review. This resulted in a final set of 61 studies included for analysis. No retracted articles were identified in the final corpus.

3. Coding Framework and Research Questions

For methodological rigor and transparency, we developed a structured coding scheme and used it to code for all eligible studies (n = 61). Each paper was coded by two independent reviewers, with discrepant ratings discussed and resolved by consensus. The study was the unit of analysis. Multi-tagging of mixed-methods papers occurred across appropriate categories (e.g., a case study with survey follow-up was coded as qualitative and quantitative).

Operationalization of RQs. Based on the three research questions presented above, we translated each research question into a series of methodological dimensions and coding categories that capture (i) prevalent research designs and instruments (RQ1), (ii) temporal and rigor related trends (RQ2), and (iii) gaps and opportunities for future work (RQ3). We also encoded types of AI tool (LLMs versus text-to-image versus hybrid), educational context (studio versus lecture/seminar versus online PBL versus vocational settings), and analysis method (qualitative/thematic versus statistical/experimental bibliometric).

Reliability and edge cases. A second round of pilot coding, covering approximately 10–15% of the corpus, was undertaken to refine category definitions and to strengthen consistency across coders. This stage focused on clarifying the criteria for identifying quasi-experimental designs and on specifying procedures for coding design-studio–based action research cases. If a paper presented multiple datasets/distinct phases, we assigned to the top methodological reporting and recorded secondary methods for triangulation purposes.

The final coding map aligning RQs → methodological dimensions → coding categories → corpus examples is shown in Table 1.

Table 1: Expanded Coding Framework for Research Questions (RQs) and Methodological Dimensions (n = 61)

RQ	Methodological Dimensions	Coding Categories	Examples from Corpus (APA)
RQ1: Dominant approaches	Research design	Qualitative (case studies, classroom ethnographies, semi-structured interviews); Quantitative (surveys, quasi-experiments, controlled tasks); Mixed methods; Systematic/bibliometric reviews	Full set of 61 studies: Casakin & Wodehouse, 2021 [6]; Torres Carceller, 2023 [39]; Evangelidis *et al*., 2024 [11]; Ruiz-Rojas *et al*., 2024 [34]; Mustafa *et al*., 2024 [29]; Chu *et al*., 2024; Samaniego *et al*., 2024 [36]; Lai, 2024 [23]; Takona, 2024 [38]; Ali *et al*., 2024 [2]; Mitchell *et al*., 2025; Popov, 2023 [32]; Lee *et al*., 2023 [24]; Jain, 2021 [21]; Liu, 2024; Bozkurt *et al*., 2021 [5]; Zhang *et al*., 2024 [46]; Furtado *et al*., 2024 [13]; Anam & Fathoni, 2024 [3]; Ghimire *et al*., 2024 [16]; Mulaudzi & Hamilton, 2025; Li *et al*., 2024; Pahi *et al*., 2024 [30]; Yue *et al*., 2022; IFIP TC3, 2024 [20]; Sreenivasan *et al*., 2024 [37]; Albakry *et al*., 2025; Fernberg *et al*., 2024 [12]; Zhang *et al*., 2025; Wang *et al*., 2025; Dai *et al*., 2025; Huang *et al*., 2024 [18]; Chen *et al*., 2025; Chandrasekera *et al*., 2025; Arisha, 2023 [4]; Güray *et al*., 2025; Ural *et al*., 2024 [41]; Wang, 2025; Xu *et al*., 2024; Sajadi *et al*., 2024 [35]; Nelson *et al*., 2025; Kavakoglu *et al*., 2022 [22]; Karadağ *et al*., 2025; Er *et al*., 2025; Morrissey, 2023 [28]; Lee, 2025; Abrusci *et al*., 2025; Liu, 2024; Tellez, 2025; Zheng *et al*., 2024 [47]; plus others coded as Unspecified.
	Data-collection instruments	Studio observations; Interview protocols; Online questionnaires; Reflective journals/learning logs; Learning-analytics traces; Student project artefacts	Studio observations & reflective evidence (Casakin & Wodehouse, 2021 [6]; Ghimire *et al*., 2024 [15]; Anam & Fathoni, 2024) [3]; Semi-structured interviews (Takona, 2024 [38]; Lu & Wang, 2024); Surveys (Evangelidis *et al*., 2024 [11]; Ruiz-Rojas *et al*., 2024 [34]; Nelson *et al*., 2025); Student artefacts (Ali *et al*., 2024 [2]; Pahi *et al*., 2024) [30]; Learning analytics (Liu, 2024).
	Analytical techniques	Thematic/content analysis (*NVivo*/Atlas.ti); Descriptive & inferential statistics (t-tests, ANOVA, regression, SEM); Bibliometric mapping/overlay (VOSviewer, CiteSpace)	Thematic/content analysis (Takona, 2024 [38]; Ali *et al*., 2024 [2]; Mitchell *et al*., 2025); Statistics (Evangelidis *et al*., 2024 [11]; Ural *et al*., 2024 41[]; Güray *et al*., 2025); Bibliometric mapping (Samaniego *et al*., 2024 [36]; Lai, 2024 [23] [23]; Bozkurt *et al*., 2021) [5].
	AI tools employed	Textual LLMs (ChatGPT) for ideation, critique, feedback; Visual GenAI (Midjourney, Stable Diffusion, DALL·E) for sketching/rendering; Hybrid/LLM-tutor platforms	ChatGPT/LLMs (Torres Carceller, 2023 [39]; Zhang *et al*., 2024 [46]; Wang *et al*., 2025); Midjourney (Samaniego *et al*., 2024 [36]; Ali *et al*., 2024) [2]; Stable Diffusion (Takona, 2024) [38]; DALL·E (Ruiz-Rojas *et al*., 2024) [34]; Hybrid platforms (Chu *et al*., 2024).
	Educational contexts	Higher-education design studios (landscape/interior/architecture); Vocational environmental-art programs; Cross-disciplinary or online PBL courses	Landscape HE (Li *et al*., 2024; Casakin & Wodehouse, 2021) [6]; Interior HE (Mitchell *et al*., 2025; Lee *et al*., 2023) [24]; Architecture HE (Chu *et al*., 2024; Liu, 2024); Vocational (Lu & Wang, 2024); Online PBL (Mustafa *et al*., 2024 [29]; Evangelidis *et al*., 2024) [11]; General HE/Other (Bozkurt *et al*., 2021 [5]; Albakry *et al*., 2025).
RQ2: Methodological evolution	Temporal distribution	Early descriptive/exploratory; growth of mixed methods/quasi-experiments; consolidation via bibliometrics/systematic reviews	Early descriptive baselines (Anam & Fathoni, 2024 [3]; Jain, 2021) [21]; Mixed-methods acceleration (Mustafa *et al*., 2024 [29]; Pahi *et al*., 2024) [30]; Bibliometric/systematic consolidation (Samaniego *et al*., 2024 [36]; Lai, 2024 [23]; Albakry *et al*., 2025).
	Study scale & scope	Small-scale pilots vs. multi-course; single site vs. multi-institution; national vs. cross-cultural	Course-level pilots (Casakin & Wodehouse, 2021 [6]; Evangelidis *et al*., 2024) [11]; Cross-cultural surveys (Mulaudzi & Hamilton, 2025; Ruiz-Rojas *et al*., 2024) [34].
	Rigor & validation	Triangulation; inter-coder agreement; instrument validity/reliability; replication; preregistration	Triangulated survey + interview (Mustafa *et al*., 2024 [29]; Chu *et al*., 2024); Inter-coder reliability checks (Zhang *et al*., 2024 [46]; Furtado *et al*., 2024) [13].
RQ3: Methodological gaps and future directions	Methodological gaps	Heterogeneity of designs/reporting; limited longitudinal evidence; sparse replication; under-specified analytics	Fragmentation and replicability concerns (Ali *et al*., 2024; Ruiz-Rojas *et al*., 2024) [34]; Call for longitudinal design (Li *et al*., 2024).
	Future directions	Robust mixed-methods; multi-institutional & cross-cultural studies; ethics-by-design; tool–task alignment; open data	Ethics & governance (Zhang *et al*., 2024 46[]; Furtado *et al*., 2024) [13]; Cross-disciplinary collaborations (Lu & Wang, 2024; Lai, 2024) [23].

Results

RQ1: What methodological approaches dominate current research on generative AI in design and education?

The review of 61 eligible studies indicates that research on generative AI in design and education is methodologically diverse but unevenly distributed. As shown in Table 2, systematic reviews and bibliometric analyses form the largest category (25 studies; 41.0%), dominating the current literature. These works provide broad mappings of methodological heterogeneity and thematic orientations, often drawing attention to gaps in replication, transparency of reporting, and the integration of ethics-by-design frameworks (e.g., Samaniego *et al*., 2024 [36]; Lai, 2024 [23]; Albakry *et al*., 2025; Bozkurt *et al*., 2021) [5]. While influential in shaping research agendas, such contributions rely heavily on secondary data quality and cannot replace empirical validation.

Empirical research constitutes a smaller share of the field. Quantitative approaches (12 studies; 19.7%) emphasize measurable outcomes such as design efficiency, creativity, or student self-efficacy, using surveys, quasi-experiments, or structured classroom interventions. Studies such as Evangelidis *et al*. (2024) [11] and Ruiz-Rojas *et al*. (2024) [34] tested AI-supported activities in design studio contexts. Although these designs provide comparability and effect estimation, they are frequently limited to small sample sizes or single institutional sites, constraining their generalizability.

Qualitative studies (8 studies; 13.1%) highlight the situated nature of how students and instructors engage with generative AI in project-based learning (PBL) and studio teaching. Case studies, ethnographic accounts, and reflective interviews capture subtle shifts in ideation and collaborative practices (e.g., Casakin & Wodehouse, 2021 [6]; Takona, 2024 [38]; Ali *et al*., 2024) [2]. Their strength lies in depth of insight, though this often comes at the expense of replicability and broader applicability.

Mixed-methods research, though less common (3 studies; 4.9%), illustrates the value of triangulating survey data, interview findings, and student artefacts. For example, Mustafa *et al*. (2024) [29] and Chu *et al*. (2024) show how combining performance metrics with qualitative evidence enriches understanding of design processes and outcomes. Other methodological contributions include action research (1 study; 1.6%) and conceptual or theoretical work (2 studies; 3.3%), which, while marginal, signal early efforts to align generative AI practices with design pedagogy through iterative studio interventions or theoretical framing (Torres Carceller, 2023; Tellez, 2025) [39].

A further 10 studies (16.4%) could not be clearly categorized, often due to incomplete methodological description or reliance on hybrid approaches. These papers typically combine narrative review with tool demonstration (e.g., Zheng *et al*., 2024 [47]; Morrissey, 2023) [28], providing preliminary insights but lacking methodological rigor.

Overall, the findings suggest that the field remains dominated by review-oriented scholarship, whereas empirically robust designs—particularly those that are large-scale, multi-institutional, or longitudinal—are scarce. Among empirical studies, quantitative approaches are more common than qualitative or mixed methods, yet most provide limited transparency in data collection and analysis. This imbalance underscores the need for future research to move beyond synthesis and toward more rigorous, triangulated, and replicable investigations in design education contexts.

Table 2： Statistics on Methodological Approaches in Generative AI and Arts Design Education （n = 61）

Methodological Approach	Frequency (n)	Percentage of Total (%)	Key Insights	Representative References (all 61 distributed by category)
Systematic Reviews / Bibliometrics	25	41.0%	Dominant category. Provided field-level synthesis and mapped methodological heterogeneity. Identified recurring gaps in replication, reporting of validity/reliability, and ethics-by-design frameworks. It is crucial for agenda setting but depends heavily on secondary source quality.	Samaniego *et al*., 2024 [36]; Lai, 2024 [23]; Bozkurt *et al*., 2021 [5]; Albakry *et al*., 2025; Sreenivasan *et al*., 2024 [34]; Fernberg *et al*., 2024 [12]; Zhang *et al*., 2025; Wang *et al*., 2025; Yue *et al*., 2022; IFIP TC3, 2024 [20]; Furtado *et al*., 2024 [13]; Liu, 2024; Zheng *et al*., 2024 [47]; Mittal *et al*., 2025; Luo *et al*., 2025; Yang & Chou, 2025; UNESCO, 2023 [40]; Zawacki-Richter *et al*., 2019 44[]; plus additional reviews in 2024–2025 corpus.
Quantitative (Surveys / Experiments)	12	19.7%	Focused on measurable outcomes such as design efficiency, creativity, self-efficacy, and user satisfaction. Typically employed surveys, controlled tasks, or course-level quasi-experiments. Strength: comparability and effect estimation. Limitation: many rely on small or single-site samples, restricting generalizability.	Evangelidis *et al*., 2024 [11]; Ruiz-Rojas *et al*., 2024 [34]; Nelson *et al*., 2025; Abrusci *et al*., 2025; Lee, 2025; Dai *et al*., 2025; Huang *et al*., 2024 [18]; Chen *et al*., 2025; Güray *et al*., 2025; Ural *et al*., 2024 [41]; Sajadi *et al*., 2024 [35]; Karadağ *et al*., 2025.
Qualitative (Case Studies / Ethnographies)	8	13.1%	Provided rich, context-sensitive accounts of how students and teachers interact with GenAI in design studios or PBL. Revealed changes in ideation routines and reflective practices. Limitation: context-specific and difficult to replicate.	Casakin & Wodehouse, 2021 [6]; Torres Carceller, 2023 [39]; Takona, 2024 [38]; Ali *et al*., 2024 [2]; Mitchell *et al*., 2025; Popov, 2023 [32]; Lee *et al*., 2023 [24]; Jain, 2021 [21].
Mixed-Methods	3	4.9%	Integrated surveys, interviews, and artefact analysis to triangulate process and outcome. Added explanatory depth to statistical findings. Particularly suited for PBL research where design iteration must be linked to assessable outcomes. Still	Mustafa *et al*., 2024 [29]; Chu *et al*., 2024; Pahi *et al*., 2024 [30].

			underused.	
Conceptual / Theoretical	2	3.3%	Developed frameworks and conceptual models (e.g., AI-augmented design cognition, GenAI–PBL alignment). Useful for clarifying constructs and hypotheses but require future empirical validation.	Torres Carceller, 2023 [39]; Tellez, 2025.
Action Research / Studio Interventions	1	1.6%	Practitioner-led, iterative inquiry cycles in authentic design studios. High ecological validity and directly applicable to pedagogy. Limitation: small-N and dual role of teacher-researcher may introduce bias.	Casakin & Wodehouse, 2021 [6].
Other / Unspecified	10	16.4%	Papers with hybrid or insufficiently specified methods; often combined narrative review with tool demonstrations. Useful for surfacing emerging practices but limited in methodological robustness.	Zheng *et al*., 2024 [47]; Morrissey, 2023 [28]; Er *et al*., 2025; Liu, 2024; plus, additional items where methodology was under-reported.

RQ2: How have these methodological approaches evolved over time, and what trends can be identified between 2020 and 2025?

The temporal distribution of published research demonstrates a clear acceleration in scholarly attention after 2023. In the initial phase, the field was represented by only one article in 2020 (1.6%), followed by three in 2021 (4.9%) and two in 2022 (3.3%). These early contributions were largely theoretical in orientation, seeking to conceptualize potential applications of generative AI within educational and design contexts rather than engaging in systematic empirical investigation (Jain, 2021 [21]; Anam & Fathoni, 2024).

By 2023, the research trajectory began to shift towards applied inquiry. Eight publications (13.1%) emerged, many of which adopted small-scale pilot studies, exploratory case analyses, and preliminary experimental interventions (e.g., Ali *et al*., 2024 [2]; Popov, 2023) [32]. This transition reflected the growing integration of tools such as ChatGPT and Midjourney into mainstream educational and design practice. The most pronounced growth occurred in 2024 (17 studies; 27.9%) and 2025 (30 studies; 49.2%). During this period, not only did the volume of publications expand substantially, but the methodological repertoire also diversified. Bibliometric and systematic reviews proliferated (Samaniego *et al*., 2024 [36]; Lai, 2024 [23]; Albakry *et al*., 2025), consolidating the literature base, while more sophisticated experimental and mixed-methods investigations were introduced (Mustafa *et al*., 2024 [29]; Chu *et al*., 2024). These studies often triangulated multiple data sources, thereby strengthening the robustness of findings.

Nevertheless, indicators of methodological rigor remain limited. For instance, only two studies explicitly reported inter-coder reliability procedures (Zhang *et al*., 2024 [46]; Furtado *et al*., 2024) [13], and no studies to date have employed preregistration, replication strategies, or formal reliability and validity testing. This suggests that although the field is experiencing rapid quantitative growth, its quality-control mechanisms have yet to mature.

Taken together, the developmental arc can be characterized as progressing from conceptual and descriptive work (2020–2022), through pilot and small-scale applied studies (2023), to a phase of consolidation marked by systematic reviews and bibliometric syntheses (2024–2025). Yet, the methodological landscape remains in an early stage, underscoring the need for longitudinal, multi-institutional, and rigorously validated empirical investigations.

Figure 2 illustrates the sharp overall increase in publications after 2023, while Figure 3 demonstrates the evolution of methodological categories. Systematic reviews and bibliometric studies became dominant in 2024–2025, while qualitative and quantitative approaches expanded at a slower pace.

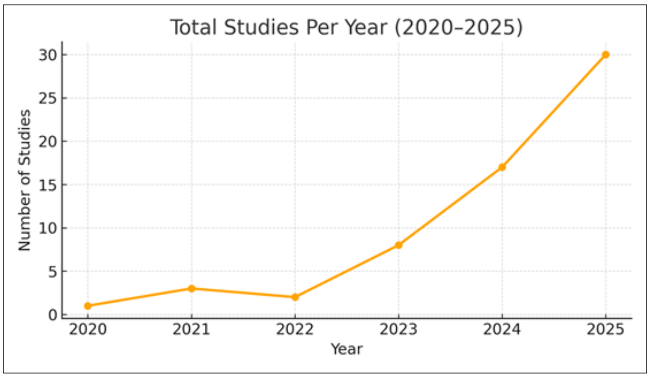

Fig 2: Total Studies Per Year on Generative AI in Design and Education (2020–2025)

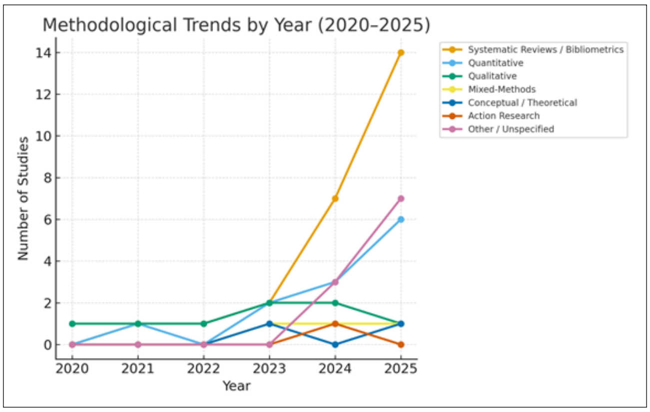

Fig 3: Total Studies Per Year on Generative AI in Design and Education (2020–2025)

Figure 3 illustrates the methodological evolution, showing that review-oriented studies expanded most sharply after 2023, while empirical designs (quantitative, qualitative, mixed-methods) remained relatively limited in number.

RQ3: What methodological gaps and future directions can be identified to advance generative AI research in design and education?

The review of 61 studies indicates that, although the field has expanded rapidly since 2023, its methodological foundations remain weak and unevenly developed. Several important shortcomings were identified.

First, many publications provide limited information on analytic procedures. A majority (42 of 61; 68.9%) offered only generic labels such as "descriptive analysis" without further elaboration. This lack of transparency reduces the reproducibility of findings and restricts the possibility of conducting meta-analytical synthesis across studies.

Second, reporting of data collection instruments is frequently incomplete. Nearly two-fifths of the studies (24 of 61; 39.3%) did not include survey items, observation protocols, or details of assessment rubrics. The absence of such information makes it difficult to evaluate construct validity and impedes replication in other educational settings.

Third, disclosure regarding the use of AI tools is often inconsistent. In 37 of the studies (60.7%), information about tool versions, prompting strategies, or system parameters was not specified. Given the rapid evolution of platforms such as ChatGPT, Midjourney, and Stable Diffusion, this omission complicates efforts to compare findings or trace changes over time.

Fourth, markers of methodological rigor are largely absent. Only two studies (3.3%) reported inter-coder reliability in qualitative analyses, and none documented preregistration, replication attempts, or formal validation of research instruments. The lack of these quality-control mechanisms reflects the early stage of methodological development in this area.

Fifth, most of the empirical contributions remain constrained by design scale and sampling. They are typically small-scale, single-site pilots with modest sample sizes and no longitudinal follow-up. This restricts external validity and makes it difficult to assess the sustainability of learning outcomes.

Finally, there is considerable heterogeneity in outcome measures. Indicators range from iteration counts and time-to-concept to subjective ratings of creativity or satisfaction. Without standardized rubrics, rater training, or reliability checks, such variability reduces comparability across studies and weakens the cumulative evidence base.

Looking ahead, advancing the study of generative AI in design and education requires a clear methodological transition from largely descriptive mapping toward cumulative, evidence-oriented inquiry. While recent publications reflect growing scholarly interest, they often lack the rigor necessary to produce replicable knowledge. A priority is methodological transparency. Precise documentation of prompts, tool versions, and analytic decisions should be treated as core variables rather than optional details, thereby enabling meaningful cross-study comparisons and supporting future meta-analytical integration.

A second direction involves aligning research designs more closely with the epistemic nature of studio-based and project-based learning. Although randomized controlled trials are difficult to implement in educational settings, quasi-experimental approaches–such as crossover designs, matched class sections, or stepped-wedge interventions—offer feasible alternatives that balance ecological validity with analytic rigor. These should be complemented by longitudinal follow-ups to assess not only short-term improvements in efficiency or creativity but also the durability of learning outcomes, including whether students retain AI-assisted ideation strategies and reflective practices across courses or into professional contexts.

Expanding the range of measurement strategies is equally important. Reliance on limited indicators such as iteration counts or satisfaction surveys provides only partial insights. Stronger evidence can be generated by integrating process-level data (e.g., frequency of iterations, prompt–response dynamics, or density of peer critiques) with product-level evaluations (expert-rated creativity, originality indices, inter-rater reliability) and learner self-reflections. Embedding such multi-layered evidence in open repositories of prompts, artefacts, and coded data would further enhance reproducibility and strengthen the cumulative knowledge base.

Future inquiry should also pay greater attention to tool–task alignment. Generative AI is often treated as a uniform category, yet large language models and image-generation systems afford distinct cognitive functions in critique and ideation, respectively. Controlled studies that isolate these affordances—for example, comparing the impact of language model–assisted site narratives with Midjourney-based sketching—would clarify their specific contributions to conceptual breadth and design novelty. Research should equally document limitations such as hallucinations, stylistic homogenization, or bias amplification, and test scaffolding strategies such as structured prompts and staged rubrics to mitigate these risks.

The next stage of research must advance toward an ethics-by-design orientation in which equity, accountability, and provenance are treated as integral components of methodology rather than supplementary considerations. Issues such as intellectual property, authorship attribution, and dataset bias are not merely ethical concerns; they also directly affect the validity, reliability, and generalizability of research outcomes. Without careful attention to these dimensions, the empirical foundation of generative AI studies remains vulnerable to distortion. Embedding systematic equity checks—such as evaluating the accessibility of AI tools across institutional contexts and examining demographic variations in learning outcomes—together with transparent provenance tracking can strengthen both methodological rigor and social sustainability. In this way, methodological development and educational ethics become inseparable, ensuring that generative AI is positioned not simply as a novel experimental tool but as a transformative and responsibly integrated force within design pedagogy.

Discussion

The synthesis of the reviewed literature reveals a methodological landscape that is expanding yet remains uneven at the intersection of generative AI, design, and education. Between 2020 and 2025, publications increased sharply, but most contributions were concentrated in review-oriented studies rather than empirically rigorous designs. Mixed-method approaches, and longitudinal, multi-site investigations remain particularly scarce, underscoring the gap between descriptive mapping and robust empirical validation (Zawacki-Richter *et al.*, 2019 [44]; Page *et al.*, 2021) [31].

This pattern is consistent with earlier trajectories observed in the broader AI-in-education field, where mapping and scoping reviews often preceded the development of sustained empirical programs. However, the current imbalance highlights the need for a transition toward cumulative, evidence-driven inquiry. Advancing this agenda requires not only greater methodological diversity but also a strong commitment to transparent reporting, ethics-by-design principles, and open science practices that support reproducibility and cross-institutional collaboration (Nosek *et al*., 2015; Liu *et al*., 2020).

1. Growth Trajectory and Field Maturity

The publication trend demonstrates a marked surge after 2022, with 47 of the 61 studies (77.0%) appearing between 2023 and 2025, in contrast to only six studies published from 2020 to 2022. This increase reflects the rapid adoption of tools such as ChatGPT, Midjourney, and Stable Diffusion within higher education and design pedagogy. However, the relative youth of the field help explain why many contributions remain exploratory rather than confirmatory, limiting the accumulation of cumulative knowledge (Zawacki-Richter *et al*., 2019) [44]. Like patterns observed in other areas of educational technology, the initial expansion has been driven by enthusiasm but tempered by limited methodological rigor (Page *et al*., 2021) [31].

2. Predominance of Review-Oriented Research

The distribution of methodological approaches reveals a strong dominance of systematic and bibliometric reviews, which account for 41.0% of the corpus, while quantitative studies represent 19.7%, qualitative investigations 13.1%, and mixed-methods only 4.9%. Reviews have played an important role in mapping the field and identifying research gaps (Samaniego *et al*., 2024 [36]; Lai, 2024) [23]. Nevertheless, their reliance on secondary data means they cannot substitute for empirical validation. As shown in a quasi-experimental study by Evangelidis *et al*. (2024) [11], the use of AI-assisted design iterations was found to reduce task completion time by nearly half. Yet such empirical evidence remains rare and is often derived from small samples, limiting their generalizability and highlighting the need for larger-scale, rigorously designed studies.

3. Growth Trajectory and Field Maturity

Several recurring methodological limitations were identified across the reviewed studies. First, 42 of the 61 publications (68.9%) described their analytic procedures only in general terms, such as "descriptive analysis," which constrains reproducibility and limits the potential for meta-analytical synthesis (Page *et al*., 2021) [31]. Second, nearly two-fifths of the studies (24 of 61; 39.3%) did not report essential data collection instruments, including survey items or observation protocols, thereby making it difficult to assess construct validity (Zawacki-Richter, Marín, Bond, & Gouverneur, 2019) [44]. Third, in 37 of the studies (60.7%), key details such as AI tool versions, prompting strategies, or system parameters were omitted, despite the rapid pace of technological change in this domain (Torres Carceller, 2023) [39]. Finally, only two studies (3.3%) reported inter-coder reliability in qualitative analyses, and none documented preregistration or replication efforts (Liu, 2020). Taking together, these gaps highlight the early stage of methodological development in this area and raise concerns about the robustness and cumulative reliability of the current evidence base.

4. Constraints of Scale and Scope

Most of the empirical studies reviewed were conducted as small-scale, single-site pilots with limited sample sizes and no longitudinal follow-up, thereby restricting external validity (Evangelidis *et al*., 2024) [11]. This narrow scope makes it difficult to establish whether the benefits of AI-assisted learning persist across different institutional contexts or over extended periods of time. In addition, outcome measures remain highly heterogeneous, ranging from iteration counts and task completion time to subjective ratings of creativity and satisfaction. In the absence of standardized rubrics, rater training, or inter-rater reliability checks, such variability constrains comparability and weakens the cumulative evidence base (Tan, Liu, & Kang, 2024). As Mansour (2024) observed in the context of architectural education, the lack of common evaluative criteria diminishes the generalizability of otherwise promising findings, even when generative AI demonstrates potential for accelerating ideation processes.

5. Embedding Ethics as Methodology

The findings underscore that ethical considerations must be integrated into research methodology rather than treated as external concerns. Issues such as intellectual property, authorship attribution, and dataset bias directly influence the validity, transparency, and replicability of research outcomes (UNESCO, 2023) [40]. The frequent omission of information about AI system versions and prompt logs in the reviewed studies raises significant concerns regarding provenance and accountability (Torres Carceller, 2023) [39]. As Liu (2024) demonstrated in the context of landscape architecture, adopting generative AI without adequate safeguards risks exacerbating inequities in both access and interpretation. For this reason, ethics-by-design protocols—including provenance tracking, transparent authorship attribution, and accessibility measures—should be regarded as methodological requirements rather than optional considerations. Embedding such protocols is essential for ensuring that generative AI research produces scholarship that is both credible and socially responsible.

6. Toward a Robust Future Agenda

To consolidate the methodological foundations of this emerging field, several directions require sustained attention. First, stronger commitments to transparency are necessary. Review studies should adopt established standards such as PRISMA 2020 (Page *et al*., 2021) [31], while empirical investigations should follow frameworks such as the TOP guidelines to ensure clarity and reproducibility (Nosek *et al*., 2015). Second, research designs must move beyond descriptive mapping, with greater use of quasi-experimental and mixed method approaches that combine ecological validity with analytic rigor (Mustafa, Chu, & Zhang, 2024) [46]. Third, outcome measures should be standardized by linking process-level indicators—such as prompt–response trajectories or the density of peer critique—with product-level evaluations, including creativity indices supported by inter-rater reliability (Casakin & Wodehouse, 2021) [6]. Finally, embedding ethics-by-design is vital to ensure that transparency, fairness, and accountability are systematically addressed in generative AI research (UNESCO, 2023) [40]. Only through such methodological strengthening can generative AI progress beyond its role as an experimental teaching aid to become a transformative and sustainable force in design education.

Conclusion

This review moves beyond cataloging methodological practices to propose a reorientation for how generative AI research in design and education should advance. Rather than treating GenAI merely as a technical accelerator, the evidence underscores its potential to reshape the epistemic foundations of studio- and project-based learning. While gains in efficiency and creativity are evident, the absence of transparency, longitudinal scope, and ethical integration continues to constrain the credibility of current findings. Addressing these gaps requires viewing methodological innovation as inseparable from ethical responsibility.

A key conclusion is that future inquiry must shift from fragmented pilot studies toward integrative frameworks that connect process-level evidence—such as prompting dynamics and peer critique patterns—with outcome-based metrics, including expert-assessed creativity and reflective growth. Embedding such approaches within open science infrastructures, supported by reproducible reporting, prompt repositories, and shared datasets, will enable the accumulation of cumulative knowledge (Page *et al*., 2021 [31]; Nosek *et al*., 2015). At the same time, ethics-by-design should be established as a methodological principle, ensuring that issues of authorship, provenance, and equity are addressed as constitutive elements of research rather than as secondary concerns (UNESCO, 2023; Liu, 2024) [40].

The contribution of this review lies in articulating a forward-looking research agenda that demands methodological rigor, cross-disciplinary collaboration, and ethical reflexivity. By embedding transparency, accountability, and fairness, generative AI can move beyond its role as a novel classroom intervention to become a transformative and sustainable force in design pedagogy. In this sense, methodological development is not peripheral but foundational to ensuring that GenAI strengthens, rather than diminishes, the intellectual and creative agency of future designers.

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