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## Generative AI-enabled chatbots for user-centred design: a state-of-the-art review

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### ABSTRACT

With the rapid advance of generative artificial intelligence (GenAI), particularly large language models, user-centred design (UCD) is transforming from static, fragmented design approaches to dynamic, interactive, and collaborative ones. Compared with traditional requirements elicitation and design support methods, GenAI-enabled chatbots provide scalable, adaptive, and context-aware support throughout the design process. This research conducts a review of relevant studies published between 2015 and 2025. It proposes an analytical framework including cognitive augmentation, collaborative facilitation, and workflow integration to explain how GenAI chatbots empower UCD across problem framing and user research, idea generation, prototype development, and iterative optimisation. The findings indicate that GenAI chatbots are evolving from conversational agents into interactive collaborators, expanding designers' capabilities in information processing, ideation, and iterative refinement. This review also highlights that such a transformation has raised challenges, including the allocation of human–AI roles, limitations in domain-specific knowledge integration, the lack of robust evaluation frameworks, and concerns around explainability, ethics, and trustworthiness. Considering these concerns, this study identifies future research directions, including hybrid human–AI collaboration models, domain-specific and multimodal knowledge support, and systematic evaluation and governance frameworks. This research not only deepens the understanding of human–AI collaborative generative intelligent design but also demonstrates the transformative role of GenAI chatbots in advancing the next generation of user-centred design.

### KEYWORDS

User-centred design; Generative intelligent design; human–AI collaboration; Generative artificial intelligence; Large language models; chatbots

## 1. Introduction

With the rapid advancement of generative artificial intelligence (GenAI), engineering design is experiencing a paradigm shift. Traditional design has largely relied on expert knowledge, rule-based reasoning, or parametric optimisation (Saadi and Yang 2023). In recent years, generative approaches based on large language models (LLMs) have been

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progressively shifting design paradigms toward human-centred generative intelligent design enabled by human–AI collaboration (Li et al. 2025a, 2025b). This approach facilitates collaboration between humans and AI, integrating expert knowledge, multimodal data, and generative algorithms to achieve automation and intelligence throughout the design process (Jin et al. 2024).

Notably, this trend aligns closely with Licklider’s vision of human–computer symbiosis, highlighting the complementarity between human creativity and value judgment and machine capacities for large-scale data storage and rapid computation (Licklider 1960). The emergence and development of generative AI is enabling the realisation of this vision, making human–AI collaboration a norm in engineering design (Bordas et al. 2024; Saadi and Yang 2023). In this context, GenAI-enabled chatbots are evolving beyond their traditional role as conversational agents into interactive collaborators that connect a variety of generative tools such as text-to-image, text-to-code, multimodal interaction (Casheekar et al. 2024). They not only enable natural language interactions for requirement elicitation and semantic clarification but also provide dynamic feedback and cognitive support in ideation, prototyping, and iterative refinement (Wang et al. 2025a, 2025b). This extends design into a more collaborative model of human–AI co-creation.

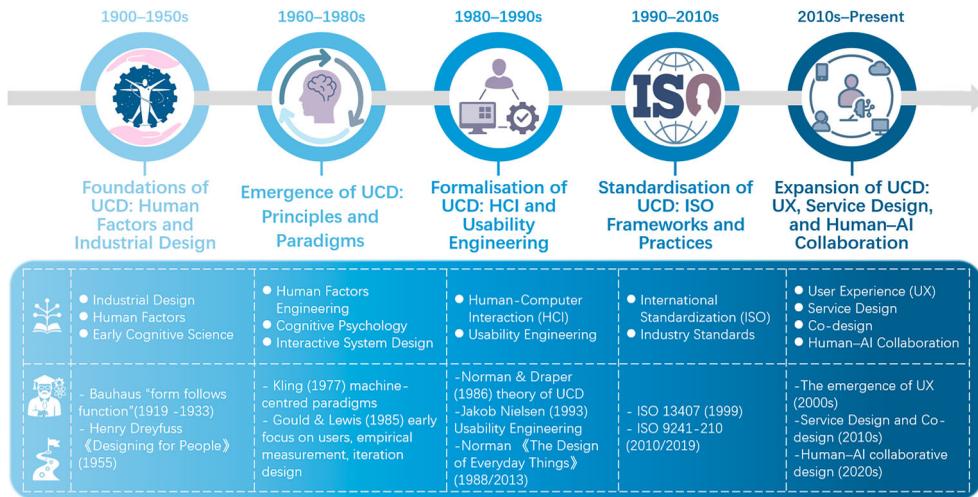
However, existing research focuses on single application scenarios or technical capabilities, lacking a systematic perspective to reveal the value and challenges of GenAI chatbots across the design process. While some reviews have explored generative models in engineering design (Regenwetter, Nobari, and Ahmed 2022) or broadly examined AI’s role in innovation management and design frameworks (Mariani and Dwivedi 2024; Singh and Gu 2012), an in-depth analysis of GenAI chatbots in user-centred design (UCD) is needed. Therefore, this research conducts a review to synthesise and critically analyze relevant research findings from 2015 to 2025. It proposes a multidimensional framework encompassing cognitive augmentation, collaborative facilitation, and workflow integration to elucidate the roles of GenAI chatbots in enabling UCD. This study aims not only to synthesise existing research progress but also to identify future directions, including issues of trustworthiness, domain knowledge embedding, multimodal integration, and ethical governance. This lays a theoretical and practical foundation for advancing human–AI collaborative design paradigms.

The structure of this paper is as follows: Section 2 outlines the theoretical foundations and emerging challenges of UCD. Section 3 presents the historical and technical development of GenAI-enabled chatbots. Section 4 provides an analysis of the literature, identifying key research themes and emerging trends. Section 5 examines how GenAI chatbots empower UCD through cognitive augmentation, collaborative facilitation, and workflow integration. Section 6 identifies key challenges and directions for future research. Section 7 concludes the paper.

## **2. Theoretical foundations and emerging challenges of user-centred design**

### **2.1. Theoretical foundations and evolution of user-centred design**

User-centred design is an interactive system design approach that integrates users’ needs, goals, and preferences throughout the entire product or system development process (Abrams, Maloney-Krichmar, and Preece 2004). It emphasises active user participation, a deep



**Figure 1.** Historical evolution of UCD.

understanding of usage contexts and tasks, and continuous iterative improvement and evaluation. This implies the need for continuous interpretation of user input, contextual coherence, and iterative feedback support rather than episodic analysis (Gulliksen et al. 2003). UCD places user experience (UX) at the forefront of design decisions, contributing to the effectiveness, user satisfaction, and long-term sustainability of products (Giacomin 2014).

Driven by sustained technological advancement and the rise of cognitive science, UCD has evolved from early humanistic design thinking to a structured design paradigm, as illustrated in Figure 1. This evolution reflects the maturation of design philosophy and a shift toward systematically acquiring, representing, and updating user information.

In the early 20th century, the Bauhaus movement marked a turning point by emphasising that design should serve human needs (Droste 2002). This view was later reinforced by industrial design pioneers such as Henry Dreyfuss, who argued in *Designing for People* that well-executed design enhances safety, comfort, and user satisfaction (Dreyfuss 1959). By the late 1970s, scholars such as Kling began to emphasise user-centred approaches to system design, critiquing the limitations of machine-centred paradigms (Kling 1977). In 1985, Gould and Lewis formally articulated the three core principles of UCD: early focus on users, empirical measurement, and iterative design (Gould and Lewis 1985). Building on this, Norman and Draper systematized the theoretical framework and process of UCD (Norman and Draper 1986). Their work highlighted the importance of aligning design with users’ mental models and usage contexts, shifting the understanding of users from static functional requirements to a context-relevant and continually evolving cognitive process.

In 1999, international standards such as ISO 13407<sup>1</sup> were released, reflecting a new phase in the evolution of UCD toward a more formalised and widely recognised design approach (Jokela et al. 2003).

During this period, UCD processes and principles were progressively clarified through research and practice, providing guidance for industrial implementation. These developments were later consolidated in standards such as ISO 9241-210<sup>2</sup>, which codified core

UCD principles and emphasised their consideration across the entire system lifecycle (Giacomin 2014). Moreover, Norman's book *The Design of Everyday Things* was influential in popularising UCD philosophy and establishing it as a foundational approach in product and interaction design (Norman 2013). In the 21st century, UCD has evolved into a new design paradigm centred on holistic UX by integrating with agile development, service design, and emotional experience (Norman 2013). It extends beyond product interfaces to address the cognitive, emotional, social, and contextual dimensions of users' interactions with products, services, and systems (Hassenzahl 2010). While this progression creates new opportunities for innovation and deeper engagement, it also brings challenges, such as the need for greater user insight, stronger cross-disciplinary collaboration, and careful cost–benefit balancing in the implementation of user-centred practices (Mao et al. 2005). As a result, greater demands are placed on technical systems for supporting user understanding and feedback iteration.

## 2.2. UCD practices and emerging technical implications

In UCD, a deep understanding of user needs forms the foundation for all design decisions and extends throughout the entire design process and product lifecycle. The process typically begins with user needs elicitation and context understanding and then advances iteratively through design representation and co-creation, as well as evaluation and continuous improvement (Abrams, Maloney-Krichmar, and Preece 2004). To support these activities, a range of methods has been developed to collect, analyze, and represent user information. As shown in Table 1, these methods can be organised by typical UCD lifecycle phases.

In the early stage of user research and context understanding, commonly used qualitative methods include interviews, focus groups, and contextual inquiries, which help uncover user behaviours, motivations, and emotions through deeper research. For example, Wilkinson et al. combined field observations, cognitive walkthroughs and focus groups for smart mobility aid projects to explore the emotional barriers and functional needs of elderly and disabled users interacting with daily assistive devices (Wilkinson and De Angeli 2014). In addition, quantitative methods such as surveys and user behaviour log analysis

**Table 1.** Methods across key UCD lifecycle phases.

UCD phase	Representative methods	Function
User research and context understanding (early design)	Interviews, focus groups, field observations/contextual inquiries, surveys, behavioural log analysis of existing systems	Identify user goals, behaviours, and constraints; understand real usage contexts to provide evidence for requirement definition and problem framing
Design representation and co-creation (design development)	Personas, user journey/experience maps, co-design workshops, low-fidelity prototyping (sketches, paper prototypes), scenario walkthroughs, role-play, simulation	Translate user evidence into stakeholder-readable representations; support cross-role alignment and solution exploration, and surface misunderstandings early
Evaluation and iterative refinement (design validation)	Usability testing, observation, interviews, questionnaires, prototype testing, expert reviews, in-context evaluation, post-deployment feedback and usage monitoring	Validate designs against realistic tasks and contexts; identify issues and drive iterative refinement, incorporating post-deployment feedback into continuous evolution

focus on structured, large-scale data collection to validate hypotheses, identify trends, and support user segmentation. For instance, Weightman et al. utilised structured questionnaires and standardised rating tools to evaluate children's comfort, gameplay preferences, and device acceptance, generating insights to optimise rehabilitation equipment design (Weightman et al. 2010). During the mid-stage of design representation and co-creation, visual modelling methods such as personas and user journey maps are employed to structure user insights and support effective communication across multidisciplinary teams. Relevant research indicates that persona methods can help teams focus on authentic user goals and reduce design bias (Miaskiewicz and Kozar 2011).

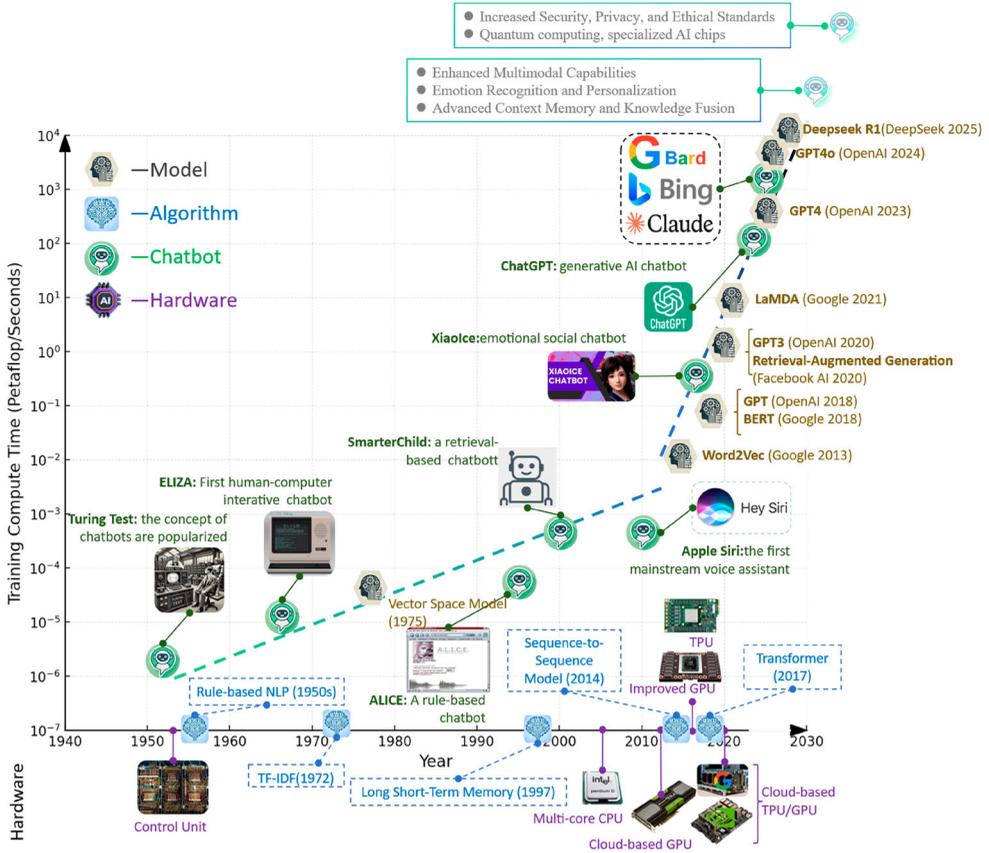
Although these traditional methods have played a crucial role in UCD, there are some challenges in the rapidly changing digital environment. In particular, many methods for eliciting and modelling user needs are applied at discrete stages of the design process, exhibiting static and lagging characteristics. These approaches often rely on one-time investigations, making it difficult to capture the dynamic evolution of user needs, behaviours, and contexts over time (Maguire 2001). Furthermore, identifying users' latent needs remains a persistent challenge. The difficulty in articulating true expectations or underlying motivations by users limits the extent to which designers can identify opportunities for innovation (Cardoso and Clarkson 2012). Meanwhile, the process from data collection to analysis and insight generation is also frequently time-consuming and resource-intensive. This stands in tension with agile development, which emphasises rapid iteration and continuous feedback (Goodman-Deane, Langdon, and Clarkson 2010). These challenges point to emerging technical needs in UCD practice, including continuous interpretation of unstructured user input, integration of heterogeneous information across stages, and timely support for iterative feedback and refinement. As artificial intelligence and other emerging technologies continue to advance, more efficient and interactive design tools and methods are being developed (Song et al. 2022). These innovations offer new opportunities for addressing the evolving nature of user needs in complex environments and expanding the potential for human–AI collaborative design (Cooper 2024).

### **3. State-of-the-art of GenAI-enabled chatbots**

#### **3.1. Evolution of chatbots towards GenAI-enabled systems**

Driven by sustained advances in computing infrastructure, algorithmic design, and data accessibility, the development of chatbots has progressed through several key stages from rule-based and retrieval-based to generative chatbots, as illustrated in Figure 2.

As early as 1950, Alan Turing proposed the Turing Test to determine whether a machine has human-like intelligence, laying the theoretical foundation for the development of natural language interaction (Turing 1950). In 1966, the first rule-based chatbot ELIZA was developed using simple pattern-matching to simulate therapeutic dialogue (Weizenbaum 1966). Despite its lack of semantic understanding and structural rigidity, ELIZA was pioneering in showing that even scripted interactions could evoke strikingly human-like responses. The early retrieval-based chatbot SmartChild, which was introduced in 2001, marked an important progression (Wu et al. 2018). Applied extensively in domains such as customer service and technical support, they represented a pragmatic balance between scalability and operational reliability. Compared to rule-based systems, they offered greater accuracy,



**Figure 2.** The evolution timeline of GenAI chatbots.

consistency and adaptability. However, these systems exhibit limitations when confronted with open-ended or complex conversations, owing to their lack of true semantic understanding and limited capacity to generalise beyond their training corpus (Manzoor and Jannach 2022).

With the development of hardware such as GPUs and TPUs, a significant increase in computational power was achieved, enabling the training of more complex and data-intensive models, which form the basis for chatbot development. In 2014, the Sequence-to-Sequence model was introduced, and in 2017, the Transformer architecture was proposed, which laid the foundation for the development of modern LLMs such as BERT and GPT (Vaswani et al. 2017; Sutskever, Vinyals, and Le 2014). These models are capable of capturing deep linguistic relationships to generate semantically rich and context-driven text. The launch of GPT-3 in 2020 represented a breakthrough in natural language generation, enabling systems to handle long and complicated conversations effectively (Brown et al. 2020). In 2023, GPT-4 further improved response accuracy and expanded multimodal capabilities to process image and text inputs (Achiam et al. 2024). The latest iteration, GPT-4o offers improvements made in 2024 to optimise conversation generation efficiency and performance (OpenAI 2024). In early 2025, DeepSeek-R1 was released by the AI startup DeepSeek, a low-cost, open-source LLM designed to enhance reasoning capabilities (DeepSeek et al. 2025).

### 3.2. Technical foundations of GenAI-enabled chatbots

Different from traditional rule-based dialogue systems, GenAI chatbots adopt a technical paradigm centred on LLMs, with interaction driven by generative and reasoning capabilities (Brown et al. 2020). Through large-scale pretraining, these systems are able to support semantic understanding, content generation, and contextual reasoning in open-ended conversations, rather than relying on predefined intent sets or fixed dialogue paths (Wang et al. 2023). The dialogue process is primarily guided by prompts and contextual information, with responses generated dynamically according to the current context (Liu et al. 2023).

The success and widespread adoption of GenAI chatbots rely on several technologies. As shown in Figure 3, their primary enabling technologies and corresponding capabilities are illustrated. Firstly, LLMs based on the Transformer architecture constitute the core cognitive and generative foundation of GenAI chatbots (Vaswani et al. 2017). They are typically pretrained on extensive corpora using self-supervised learning with deep neural

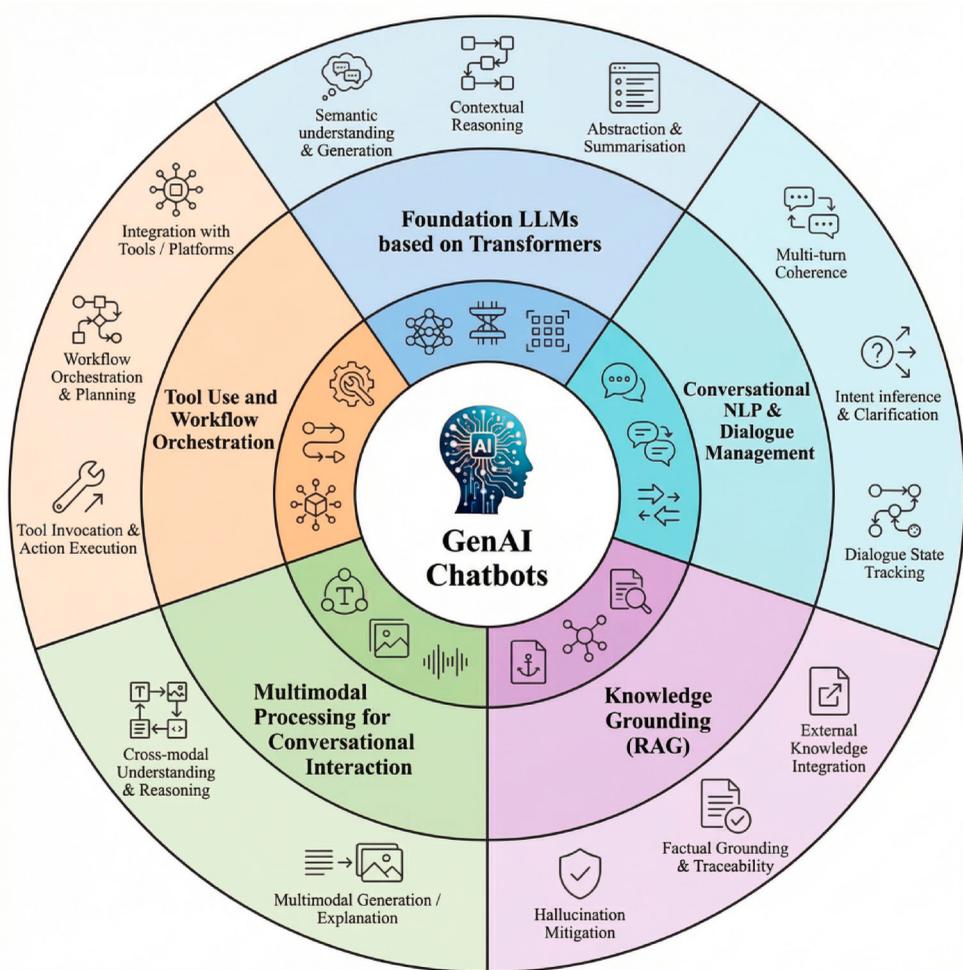


Figure 3. Technical foundations and capability framework of GenAI-enabled chatbots.

networks, allowing the models to learn semantic structures and contextual dependencies in natural language. As a result, they acquire capabilities in semantic understanding, text generation, and a certain degree of contextual reasoning and abstraction (Vaswani et al. 2017). On this basis, fine-tuning for specific tasks or application scenarios further optimises model behaviour to better align with practical requirements (Lu, Luu, and Buehler 2025). In addition, the incorporation of reinforcement learning and optimisation strategies based on human feedback helps adjust response preferences and improve generation stability, making these models more suitable for human–AI interaction (Junping Zhang et al. 2023).

Furthermore, the technology of natural language processing (NLP) provides essential support for multi-turn interactions (Zhang et al. 2025). Through natural language understanding and natural language generation, the system can interpret the semantic intent of user inputs while maintaining linguistic coherence in generated responses (Khurana et al. 2023). At the same time, dialogue management regulates the coordination and control of interactions between GenAI chatbots and users. It ensures dialogue continuity and relevance by monitoring and updating the conversation status, a process facilitated by dialogue state tracking. In addition, dialogue policy optimisation techniques are adopted to refine response strategies based on user interaction data to improve response efficiency and personalised interaction in various applications (Casheekar et al. 2024).

In practical applications, GenAI chatbots commonly incorporate external, verifiable knowledge sources through retrieval-augmented generation (RAG) (Lewis et al. 2020). By retrieving relevant information from the knowledge base and feeding it into the model as contextual input, the generated responses are grounded in factual information. This approach partially addresses the limitations of the model's inherent knowledge, enhances the factual consistency and traceability of generated content, and mitigates risks arising from generative uncertainty (Gao et al. 2024). In addition, multimodal processing for conversational interaction expands the capabilities of GenAI chatbots to handle diverse information formats (Lu et al. 2019). By integrating text, images, or voice across multiple modalities, systems can understand and generate cross-modal content during conversations, enabling alignment and conversion across different information representations. This provides the technical foundation for more complex interaction forms.

Additionally, GenAI chatbots can invoke external tools during interaction to enhance cognitive and reasoning support, thereby improving the accuracy and reliability of their responses (Schick et al. 2023). For instance, they can selectively incorporate outputs from external function tools based on task requirements, integrating them into the subsequent generation process to improve accuracy in precise computations. This capability allows GenAI chatbots to not only facilitate conversations through dynamic interactions but also decompose complex tasks into executable steps, enabling coordination across systems and supporting complex task handling. This approach enhances their operational feasibility and scalability at the system level, providing technological support for their application in task-oriented interaction scenarios (Xi et al. 2025).

#### 4. Literature analysis and key findings

To investigate how GenAI chatbots support UCD, this study analyzes relevant research literature published between 2015 and 2025. Related studies primarily come from mainstream journals and conferences in engineering design, human–computer interaction, and

artificial intelligence fields, reflecting the interdisciplinary nature of the research area and the convergence of multiple disciplines. In recent years, driven by the advancement of technologies such as LLMs, research in this area has grown rapidly and has emerged as a prominent research topic since 2023. The selected literature spans 25 countries, indicating the global research interest and practical relevance of this topic.

#### **4.1. Synthesis of GenAI-enabled chatbot applications in UCD**

To examine the application of GenAI chatbots in UCD, this research adopts a design process perspective to structure the analysis. The main stages of design activities include problem framing and user research, ideation and concept generation, prototyping and design representation, and evaluation and iteration. This classification aligns with the core activities commonly used to structure UCD processes (Gulliksen et al. 2003).

Table 2 summarises the application of GenAI chatbots across different UCD phases. During problem framing and user research, relevant studies primarily focus on identifying user needs, clarifying requirements, and constructing user personas. They show how GenAI chatbots support the understanding of user goals and latent needs through conversational interaction, semantic reasoning, and virtual user simulation (Pan et al. 2025; Ataei et al. 2025). Moving into the ideation and concept generation phase, the research focus shifts toward supporting a concept exploration process that balances divergence and convergence. GenAI chatbots are typically employed to expand creative spaces, organise the co-evolution of problems and solutions, and facilitate multi-party collaboration (Filippi 2023; Xu et al. 2024).

In the prototyping and representation phase, existing research concentrates more on the generation and translation of specific design outputs. Such work highlights the role of GenAI chatbots in supporting rapid prototyping, user journey visualisation, and interactive refinement through conversational and multimodal generation methods (Liu et al. 2025; Li et al. 2025a, 2025b). During the evaluation and iteration phase, GenAI chatbots primarily support the collection, organisation, and analysis of UX feedback. They assist in the continuous refinement and optimisation of design solutions through dialogue and workflow-embedded interactions (Xiao et al. 2025). In addition, some studies adopt a cross-stage perspective to examine the roles, trust, and governance of GenAI chatbots in design.

Overall, existing research on GenAI chatbots in UCD is unevenly distributed across different design stages. More studies focus on early-stage design activities, particularly problem framing, user research, and ideation, with particular attention to how GenAI chatbots support need understanding and information analysis. In contrast, relatively fewer studies address the prototyping and evaluation stages. These studies tend to emphasise the generation of specific design outputs or the provision of feedback support, while system-level integration still needs further investigation. Meanwhile, some studies adopt a cross-stage perspective to explore the overall roles and principles of GenAI chatbots across the design process, providing theoretical support for their sustainable application in design practice.

#### **4.2. Research themes and cluster insights**

To uncover the conceptual structure of GenAI chatbots and UCD, a co-occurrence keyword and clustering analysis was conducted using CiteSpace, a Java-based scientific

**Table 2.** Overview of GenAI-enabled chatbot capabilities across different UCD stages.

UCD stage	Typical design focus	GenAI capability	Relevant studies
Problem Framing & User Research	User needs elicitation, requirement clarification, persona construction, and early-stage understanding of user goals and latent demands	Scalable virtual user simulation, knowledge-guided semantic reasoning, conversational qualitative inquiry, and interactive persona generation	Ruan, Chen, and Jin (2023), Liu and Martens (2024), Pan et al. (2025), Ataei et al. (2025), Zhuang et al. (2025), Zhu et al. (2025), Zhou et al. (2025a, 2025b, 2025c), Arora, Chakraborty, and Nishimura (2025), (Wang et al. 2025a, 2025b)etc.
Ideation & Concept Generation	Support divergent and convergent conceptual design by expanding idea spaces, structure problem-solution co-evolution, and accelerate collaborative decision-making	Large-scale idea exploration through conversational and multimodal generation, data-informed concept refinement, and human–AI co-creation through interactive, workflow-integrated dialogue	Zhu and Luo (2022), Filippi (2023), Xu et al. (2024), Gao and Li (2025), Li et al. (2025a, 2025b), Zhou et al. (2025a, 2025b, 2025c), Chen et al. (2025), etc.
Prototyping & Representation	Rapid prototyping, user journey mapping, visual storytelling, and interactive artefact refinement	Conversational and multimodal prototyping for human–AI co-creation, prompt-based generation, and iterative integration of design intent, feedback, and control	Wang et al. (2024), Antony and Huang (2024), Mei et al. (2025), Liu et al. (2025), Subramonyam et al. (2025), Li et al. (2025a; 2025b), etc.
Evaluation & Iteration	UX evaluation, iterative feedback incorporation, and design refinement	Conversational feedback, mixed-initiative prompting, iterative UX validation, and workflow-embedded design making	Kuang et al. (2023), Duan et al. (2024), Feng et al. (2025), Xiao et al. (2025), Zhao et al. (2025), Kim et al. (2025), (Zhou, Zhang, and Yu 2025c), etc.
General / Cross-stage Applications	Cross-stage guidance and governance, human–AI role, organisation principles and workflows	Conversational assistance, multimodal content generation, workflow-embedded co-creation, trust, controllability, and ethical support	Saadi and Yang (2023), Weisz et al. (2024), Jin et al. (2024), Huang et al. (2024), Bordas et al. (2024), Lee, Law, and Hoffman (2025), etc.



**Table 3.** Summary of the identified clusters.

Group	Cluster ID	Cluster topic	Size	Silhouette
Modelling and design	#2	Requirements modelling	20	0.875
	#6	Ideation quality	9	0.898
	#7	Enhancing design brief creation	8	0.89
Collaboration	#1	Designing context-aware LLM chatbot	20	0.806
	#5	Empirical case study	12	0.822
	#4	Integrating generative artificial intelligence	12	0.709
Intelligence	#0	Data-driven generative design	28	0.87
	#3	Generative transformer	15	0.937

design brief creation (#7). These clusters highlight how GenAI chatbots assist in eliciting, analyzing, and structuring user needs, while stimulating creative ideation and supporting the preparation of design briefs. Such studies underscore the role of GenAI chatbots in capturing user insights and shaping the early stages of the design process. The Collaboration group examines the integration of generative AI into co-design and real-world design practice. It includes designing context-aware LLM chatbots (#1), empirical case studies (#5), and integrating generative artificial intelligence (#4). Research in this category explores GenAI chatbots as active partners in human–AI design, enabling multi-actor collaboration, embedding GenAI into co-design workflows, and providing empirical assessments of collaborative approaches. Finally, the Intelligence group reflects advances in GenAI technologies and their transformative implications for design innovation. This group brings together data-driven generative design (#0) and generative transformer (#3), with studies addressing the technical evolution of GenAI systems, their capacity for automated design generation, and the emergence of new design paradigms. These clusters illustrate how technological progress is expanding the scope of design intelligence and driving innovation.

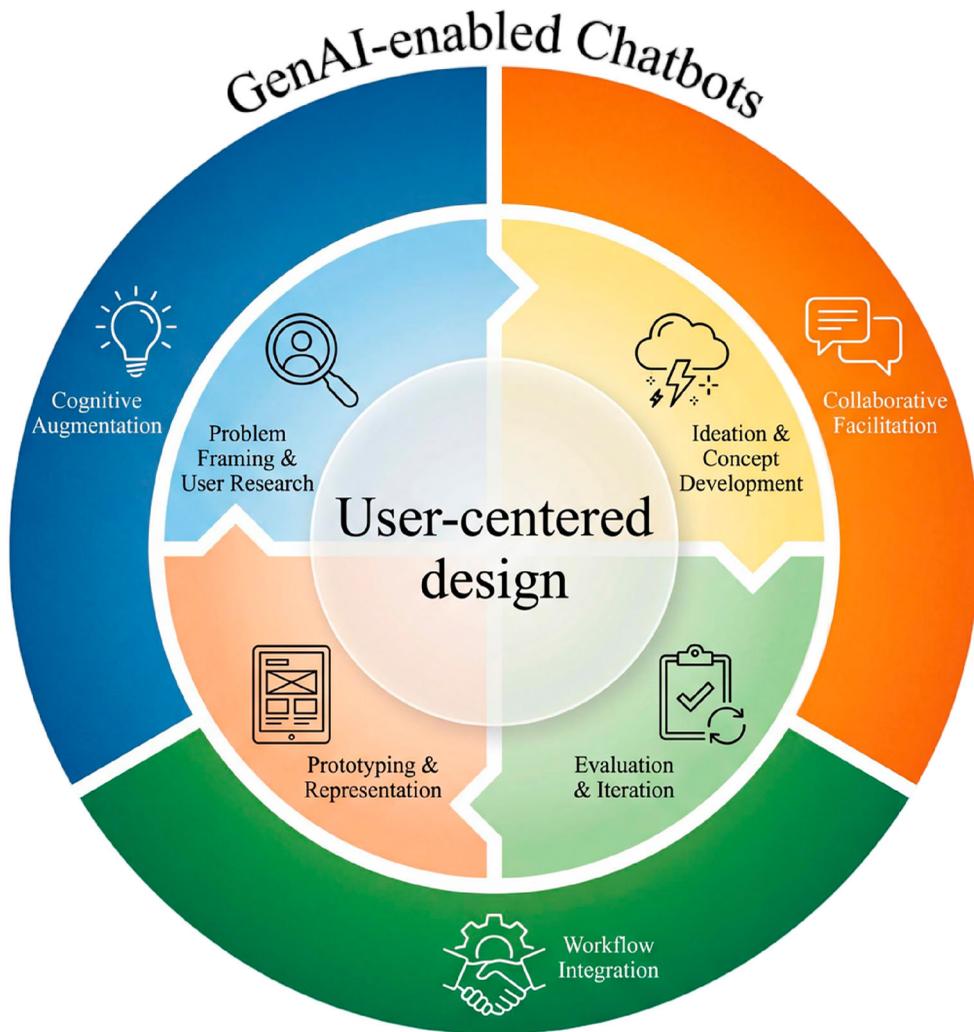
## 5. GenAI-enabled chatbots empowering user-centred design

Based on the literature analysis, GenAI-enabled chatbots demonstrate diverse functions across different stages of UCD. However, these roles are often discussed in a fragmented manner across studies, lacking a coherent perspective to systematically explain their impact within the design process. To address this, we propose a mechanism-based conceptual framework that identifies three representative ways in which GenAI chatbots empower UCD: cognitive augmentation, collaborative facilitation, and workflow integration, as illustrated in Figure 5. These mechanisms reveal how GenAI chatbots support design practices, such as structuring information and clarifying user needs, enhancing co-creation through dynamic interaction, and embedding generative capabilities into existing workflows for greater efficiency and continuity. The following subsections analyze their contributions across the design process of problem framing and user research, ideation and concept development, prototyping and representation, evaluation and iteration.

### 5.1. Intelligent partners for problem framing and user research

#### 5.1.1. Intelligent and scalable user needs elicitation

Traditional approaches to eliciting user needs, such as interviews, surveys, and field studies, are often time-consuming, labor-intensive, and limited in their ability to capture latent



**Figure 5.** Enabling mechanisms of GenAI-enabled chatbots in UCD.

needs. GenAI chatbots are empowering the user needs elicitation process, enabling it to scale with greater diversity and adaptability to dynamic contexts. Firstly, multi-agent LLM frameworks enable the creation of virtual user agents with diverse perspectives, through which experiences and feedback can be simulated. This process identifies substantially more latent needs than conventional interviews, while reducing cost (Ataei et al. 2025). Compared to interviews with a few dozen real participants, LLM-based agents can scale to hundreds or even thousands, improving coverage and representativeness. Moreover, systems like Needs Companion combine virtual agents with large models to continuously monitor user needs, enabling real-time and iterative capture in dynamic settings (Nakata et al. 2024). Additionally, conventional questionnaires are typically static. By contrast, GenAI-enabled questionnaire generation systems (e.g., UEQ-mLLM) can integrate users' emotional states, attentional focus, and contextual factors to produce highly personalised surveys (Kim et al. 2024). This makes it possible to capture subtle nuances in

UX more precisely. Finally, emerging research indicates that LLMs enable the inference of users' underlying psychological needs and goals from reviews and textual data, achieving empathic accuracy comparable to that of human designers (Zhu and Luo 2024; Zhu et al. 2025).

### **5.1.2. Semantic support for user modelling and persona generation**

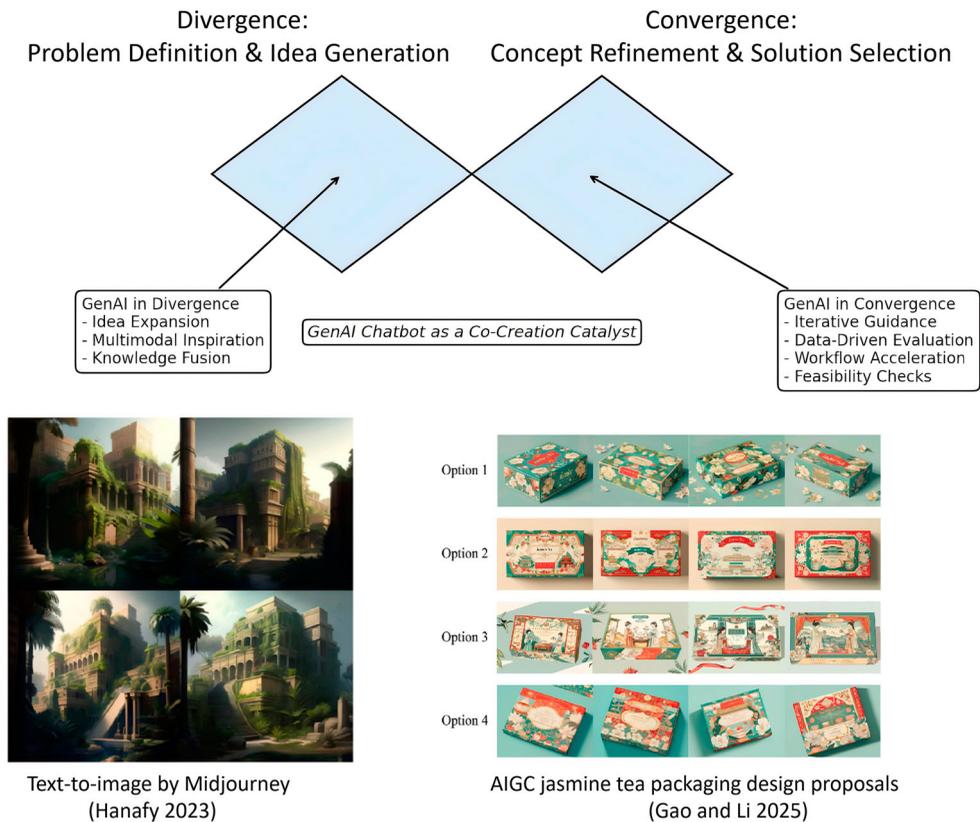
The creation of user personas typically relies on qualitative interviews and surveys, with researchers manually synthesising information. This method is time-consuming and hinders the rapid generation of diverse personas. The adoption of GenAI chatbots is shifting user modelling from static representations into more semantic and dynamic forms. Firstly, LLMs can automatically generate personas based on prompts, achieving quality and acceptance comparable to manually created ones (Schuller et al. 2024). Moreover, the Vector Personas process proposed by Lauer et al. combines the breadth of AI with the depth of human interviews to enhance credibility while ensuring character richness (Lauer, Storey, and Soley 2024). Meanwhile, immersive persona tools such as Vivid-Persona use generative models and interactive interfaces to create user personas with dynamic expressions and emotional feedback, which greatly enhances designers' empathy (Zhou et al. 2025a, 2025b, 2025c). These advancements indicate that GenAI chatbots not only support the rapid generation of user personas but also endow them with semantic depth and interactivity, offering designers new pathways to understand user needs.

### **5.1.3. Interactive collaboration for needs clarification**

Through multi-turn dialogue and interaction, GenAI chatbots are improving the way designers conduct problem framing and user research. In contrast to traditional tools that merely collect information, these systems actively guide users in articulating their needs through follow-up questions, paraphrasing, and contextual reasoning. This process enables users to clarify vague ideas and latent preferences, which effectively addresses the limitations of static questionnaires or interviews (Liu and Martens 2024). Moreover, integrating GenAI chatbots into immersive environments such as mixed reality enables users to interact with AI in real-world contexts, supporting more efficient need validation and iteration (Chen et al. 2024). This combination not only makes users feel more immersed and engaged but also provides an experiential approach to problem exploration, allowing designers and users to jointly refine requirements in dynamic settings. Furthermore, in personalised design scenarios, LLM-driven multi-agent systems demonstrate collaborative advantages. By combining knowledge graphs with large-model reasoning, they can achieve fine-grained mappings between user needs and functions and generate more targeted conceptual solutions (Pan et al. 2025). However, it is worth noting that the elicitation of user needs cannot rely solely on GenAI chatbots. There is an essential need for designers' supervision and critical judgment to ensure reliability, contextual relevance, and ethical integrity.

## **5.2. Creative catalysts for ideation and concept development**

Research indicates that the ideal process of conceptual design is not completed in a single step but rather through multiple iterations of divergence and convergence (Liu, Chakrabarti, and Bligh 2003). GenAI chatbots are increasingly acting as creative catalysts in



**Figure 6.** GenAI tools as a creative catalyst for ideation and concept development.

this dual process, enabling divergent idea exploration in the early stages while supporting convergent concept evaluation later on, as shown in Figure 6.

Firstly, with the support of GenAI tools, divergent ideation can achieve greater quantity and novelty. Traditional brainstorming is often constrained by time, limited knowledge, and mental biases, whereas GenAI-enabled chatbots not only generate numerous ideas in a short time but also guide designers through multi-turn dialogues to clarify and refine them. For example, in architectural design, text-to-image tools such as Midjourney and DALL-E 2 can quickly generate diverse visual solutions during the conceptual phase, providing designers with a broader exploration space (Ploennigs and Berger 2023). Similarly, trained on patents and award-winning designs, Transformer-based generative models can produce highly novel concept descriptions, effectively extending the boundaries of human knowledge (Zhu and Luo 2022). This improvement is largely driven by GenAI's advantages in multimodal and cross-domain integration. The latest research has moved beyond single-modality generation and begun to explore the collaborative integration of multimodal and professional tools. For example, the problem-solution co-evolution GPSdesign method organises human-AI co-creation content through a network node structure, making the design space more extensive and traceable (Chen et al. 2025). In product appearance design, combining Stable Diffusion with ChatGPT enables the generation of diverse 2D images tailored to user needs. When further integrated with software such as Rhino for 3D

modelling, this creates a complete workflow from user needs to visuals to structure (Mu 2024).

More importantly, GenAI chatbots serve as enablers of collaborative co-creation and cognitive support. Unlike single-purpose generative tools, chatbots help designers clarify vague ideas and adjust creative directions through dynamic interaction, thereby guiding toward more feasible solutions. For example, Gao et al. proposed an AI-driven tea packaging design workflow in which GenAI tools were employed for divergent idea generation, followed by structured evaluation to converge on the optimal design by synthesising expert, consumer, and market perspectives (Gao and Li 2025). Additionally, a recent comparative study showed that human collaboration with ChatGPT did not show significant improvement over humans working alone in terms of creativity. However, it substantially reduced overall design time and minimised process steps, especially in the transition from conceptualisation to realisation (Zhou et al. 2025a, 2025b, 2025c). These results indicate that GenAI chatbots can serve as accelerators for ideation and facilitators of concept refinement.

### **5.3. Conversational prototyping assistants for representation and development**

In the UCD process, the prototyping and representation stage is a critical step in transforming user needs into concrete, visual, and interactive forms. GenAI chatbots have the potential to accelerate prototype development, expand the diversity of representations, and drive the design process toward human–AI collaboration. Firstly, GenAI chatbots lower design barriers and improve efficiency through automated assistance. For example, the application of ChatGPT in enterprise UX design has reduced the time required to create design briefs by nearly 50%, while enhancing user satisfaction and information integration capabilities. However, issues such as decreased accuracy and verbosity have also emerged (Zhu et al. 2024). Moreover, the GeneyMAP tool, powered by GPT-4 and DALL-E, has decreased the effort required for creating user journey maps and increased their novelty and comprehensiveness. However, it still faces limitations such as inaccurate information mapping and insufficient designer involvement (Mei et al. 2025).

Moreover, traditional prototyping is often constrained by designers' proficiency with tools and a reliance on singular visual thinking, whereas GenAI chatbots can seamlessly integrate multimodal information to create richer, more expressive prototype forms. For example, Antony et al. introduce a design system that integrates ChatGPT, Stable Diffusion, and AudioGen to support human–AI collaboration across scripting, storyboarding, and media generation, effectively transforming static storyboards into dynamic multimedia experiences (Antony and Huang 2024). Trappey et al. further demonstrated that GPT-4o can automatically extract technical steps from patent texts and generate intuitive flowcharts, which transform complex descriptions into clear visual representations and enhance comprehension efficiency (Trappey et al. 2025). Moreover, GenAI chatbots are increasingly empowering the design process through human–AI collaboration. Subramonyam et al. highlight the role of prompt design as a critical skill in GenAI-assisted prototyping (Subramonyam et al. 2025). Li et al. introduce the system RealtimeGen that allows designers to interact in real time during AI image generation, demonstrating improvement in user experience, creative control, and efficiency (Li et al. 2025a, 2025b). This collaboration not only accelerates design workflows but also ensures that the final output meets human emotional and aesthetic needs.

### **5.4. Evaluation companions for iterative refinement**

Evaluation and iteration are core components that ensure continuous product optimisation and alignment with user needs. GenAI chatbots are emerging as promising evaluation companions in this phase. By providing support for rapid feedback, simulating virtual users, and integrating multimodal data, they can lower evaluation costs and speed up iteration cycles, while improving the reliability of design decisions. First, GenAI chatbots can support low-cost, low-risk iterations of user studies in the early stages. For example, Xiao et al. used GPT-4 to generate scripts, UI prototypes, and storyboards for the 'Air Taxi Journey' while simulating 72 virtual users answering the same questionnaire to examine the feasibility of LLMs in modelling participant responses (Xiao et al. 2025). By simulating user behaviour with LLMs, designers can conduct low-cost pre-validation before real-user studies to identify optimal design solutions. However, it is important to note that this process cannot replace real-user evaluations.

Additionally, GenAI chatbots enable the analysis of unstructured data such as interview transcripts and questionnaire responses by extracting user pain points, synthesising key themes, and generating structured reports (Siddharth, Blessing, and Luo 2022). For example, the research by Zhao et al. leveraged LLM models to enhance visual analytics by improving comprehension and insight discovery, which can be applied to the analysis of user feedback (Zhao et al. 2025). Moreover, Kim et al. compared different interaction modes and found that AI–human collaborative approaches outperformed the user-only mode in terms of output quality and prompt efficiency, further validating the value of GenAI in reducing cognitive load and enhancing creative efficiency (Kim et al. 2025).

## **6. Discussion and future directions**

This study proposes an analytical framework that provides a systematic perspective for understanding the role of GenAI chatbots in UCD, laying a structured foundation for future research. Notably, the role of GenAI chatbots does not replace the designers but rather expands their capabilities, inspiring greater creativity and improving creative efficiency. Moreover, this integration also represents a shift in the mode of collaboration. Designers are not only expected to connect users and products but also to coordinate a human–AI collaborative relationship. This positions GenAI chatbots as collaborative partners in the design process, driving UCD toward a more dialogical and iterative practice in which human creativity and AI capabilities complement one another. However, how GenAI chatbots can be better embedded into UCD workflows, and to what extent they should be integrated, still needs further investigation. The key challenges and future research directions will be discussed in the following sections.

### **6.1. Key challenges**

#### **6.1.1. Human–AI collaboration in sustaining user-centred design**

Despite the empowering potential of GenAI chatbots in UCD, their integration also presents some challenges. First, the core principle of UCD is to remain user-centred, emphasising that design should begin with user needs. However, heavy reliance on generative models for user modelling, needs identification, and idea generation may reduce direct user

involvement and overlook under-represented groups (Amin et al. 2025). Although these technologies aim to enhance the efficiency of understanding users, they may also shift the design focus away from direct engagement with real individuals toward AI-generated content. In addition, while the adoption of GenAI chatbots expands designers' capabilities in information integration and creative generation, it also places higher demands on them. Designers need to leverage the strengths of GenAI while maintaining control over critical judgment, ethical considerations, and design decisions. Thus, how to allocate human–AI responsibilities and establish complementary relationships across UCD's design phases remains an unresolved key challenge (Fang et al. 2025).

### **6.1.2. Contextual adaptation and domain knowledge limitations**

Although GenAI chatbots demonstrate efficiency advantages in design processes, they remain fundamentally grounded in general-purpose large models. Their knowledge base is extensive but lacks depth and precision in specific domains. As a result, when generating professional design content, their outputs may exhibit superficial plausibility but in fact remain generalised, failing to capture domain-specific tacit knowledge and critical constraints (Huang et al. 2023). Furthermore, design is not merely a matter of logical construction but also a process of empathetic response to complex user needs. While GenAI chatbots can simulate an understanding of user needs through pattern recognition, they may not reliably capture users' emotional fluctuations, cultural contexts, and latent needs. Therefore, reliance on such GenAI tools may produce design proposals that appear functionally feasible but lack emotional resonance and human-centred care, ultimately deviating from the essence of UCD.

### **6.1.3. Insufficient evaluation frameworks and standardisation**

Despite the growing recognition of GenAI chatbots in empowering UCD, systematic frameworks to evaluate their contributions within design processes have yet to be established. Existing studies focus on small-scale exploratory experiments or short-term case studies. They are often conducted within specific settings and tasks, making it difficult to ensure comparability, reproducibility, and generalizability of the results. In addition, current evaluations are mainly concerned with efficiency gains or functional feasibility. However, they rarely adopt multidimensional assessment frameworks that consider critical aspects such as user experience, creativity stimulation, user trust, and ethics (Shneiderman 2020). More critically, the value of GenAI chatbots often lies in complex human–AI interactions and contextual embedding, where impacts are highly dynamic and context-dependent. This makes quantitative measurement and cross-study comparison particularly challenging.

### **6.1.4. Explainability, ethics, and trustworthiness issues**

As GenAI chatbots provide users with design support, ensuring system reliability and ethical compliance becomes critically important. However, in the processes of design generation, they often function as 'black boxes,' making it difficult for designers to understand or verify the underlying logic. This lack of explainability weakens designers' control over outcomes and increases design risks. At the same time, inherent biases in training data may be amplified, leading to distorted or unfair design results. Moreover, factual errors in outputs not only undermine the reliability of design decisions but may also bring serious ethical and legal risks. More critically, design activities often depend on sensitive user data, while GenAI

tools face challenges in data storage, access, and use with respect to privacy and security. Without robust compliance mechanisms and transparent standards, it will be difficult for both users and designers to build trust in AI systems (Kaur et al. 2023).

## **6.2. Future research directions**

### **6.2.1. Toward human–AI collaboration in UCD**

To leverage the complementary strengths of GenAI chatbots and designers in UCD, future research should remain grounded in user-centred principles and advance effective human–AI collaboration models. To ensure that chatbots play an augmenting role rather than replacing designers, the investigation of collaboration frameworks and the definition of appropriate modes and boundaries of human–AI collaboration across different stages of UCD are of great significance (Fang et al. 2025). This approach allows GenAI chatbots to leverage their strengths in large-scale processing and rapid generation, while designers maintain control over value judgments, design logic, and user insights. Specifically, future work can examine which tasks are well suited for GenAI chatbots across phases such as user research, problem definition, ideation, concept refinement, and iterative evaluation. It should also clarify which steps need to remain human-led, with designers providing oversight and critical judgment (Guo and Tang 2026).

In addition, overreliance on AI-generated insights risks overlooking genuine user needs (Romeo and Conti 2025). Therefore, it is essential to explore hybrid user research methods, combining AI-generated insights to broaden design perspectives with real user feedback for validation and refinement (Amin et al. 2025). Future research can focus on how to keep real users involved at key points while integrating GenAI chatbot support. For example, this can be achieved through user verification and feedback loops to ensure generated content does not replace user input and evidence. At the same time, future work should address representation gaps that may arise from algorithmic bias. It can investigate how to better incorporate the perspectives of minority and marginalised groups during data collection and interaction processes, preventing their needs and experiences from being overlooked.

### **6.2.2. Toward contextual and domain-specific generative design**

To enhance the usability of GenAI chatbots in specific design scenarios, future research should strengthen the integration of domain knowledge support and constraints, allowing outputs to transition from conceptual descriptions to implementable design outputs. During the conceptual design phase, existing studies have demonstrated that prompts and task guidance methods impact the concept generation effectiveness and collaboration quality of LLMs (Tian et al. 2024). Therefore, it is necessary to further investigate prompt strategies and interaction paradigms tailored to different design tasks, so that chatbots can provide reliable support for activities such as idea generation. Research indicates that GenAI chatbots are better suited for handling well-defined, manageable subtasks within engineering design processes, gradually converging toward executable solutions through iterative feedback (Ege et al. 2025). Based on this, how design tasks can be decomposed into appropriate step-by-step processes to maximise the role of LLMs remains a direction worthy of further research. Additionally, future research can explore how to integrate specialised

corpora, tacit knowledge, and key constraints into models, for example through retrieval-augmented generation (Siddharth and Luo 2024). This will enable them to generate more precise, actionable, and domain-specific design solutions.

### **6.2.3. Multimodal and affect-aware support for design interactions**

To enhance GenAI chatbots' ability to understand user needs and task contexts in UCD scenarios, further research is needed on the combination of multimodal inputs, such as physiological signals and emotional cues with LLMs. Rather than relying solely on text-based interaction, GenAI chatbots can also incorporate cues such as voice intonation, facial expressions, body language, and interaction behaviour trajectories. Such integration can support reliable judgments regarding user intent, attention shifts, and emotional fluctuations, facilitating contextually appropriate responses and design support (Poria et al. 2017). In addition, prior studies show different interaction modalities and user emotional states influence users' empathic perception of conversational agents and overall interaction experience (Gao et al. 2025). Therefore, future research should explore the mechanisms of multimodal integration across different design phases to support more coherent collaboration and communication (Wang, Yang, and Yu 2026; Chen et al. 2026). Furthermore, research on affective computing and empathy modelling is essential to assess how GenAI chatbots handle issues of cultural sensitivity, emotional adaptability, and empathetic responses during interaction. Such advances may help prevent responses that appear functionally plausible but lack deeper human understanding.

### **6.2.4. Establishing evaluation frameworks and benchmarking standards**

To tackle the lack of evaluation frameworks and insufficient standardisation in existing studies, future research should develop systematic assessment methods and benchmarking systems to evaluate the contributions of GenAI chatbots in UCD. Firstly, it is necessary to establish a set of multidimensional evaluation metrics that take into consideration not only design efficiency and functional feasibility but also important dimensions such as user experience, creativity stimulation, user trust, and ethical compliance (Van Remmen, Wartzack, and Miehl 2025). In terms of design output quality, evaluation can be conducted based on novelty, usability, diversity, and the degree to which key constraints are satisfied, drawing on established metrics and prior experience from research on design creativity and novelty assessment (Shah, Smith, and Vargas-Hernandez 2003). In addition, future work should explore dynamic, workflow-based evaluation methods that can capture the impact of contextual embedding and the evolution of human–AI collaboration, ensuring the results closely align with real-world scenarios. In this regard, the evaluation framework can be validated and refined through case studies. For instance, the effectiveness and applicability of evaluation metrics can be examined through longitudinal user experiments and comparative analyses conducted in domain-specific design tasks. Through these efforts, future evaluation frameworks and benchmarking standards will facilitate the long-term reliable application and widespread adoption of GenAI chatbots in UCD.

### **6.2.5. Enhancing explainability, ethics, and trustworthiness**

To enhance the applicability and accuracy of GenAI chatbots in UCD, future research could focus on developing explainability tools tailored to design tasks. Such tools should enable

designers to understand and verify the underlying logic of AI outputs, improving transparency and controllability (Haque, Islam, and Mikalef 2023). For example, explainable mechanisms can be introduced around the design generation process to clarify the user inputs, design constraints, and external knowledge underlying design suggestions. At the same time, it is important to investigate bias detection and mitigation mechanisms to reduce the accumulation of errors from training data and model outputs, and to prevent unfair or high-risk decisions resulting from factual inaccuracies (Kaur et al. 2023). Furthermore, UCD scenarios often involve real user data and sensitive design information, ensuring user privacy and data security is essential. This requires the establishment of compliance mechanisms and transparent standards for data storage, access, and use, which provide a foundation of trust for users and designers (Leschanowsky et al. 2024). To this end, research can further integrate ethical review, privacy protection, and trustworthiness requirements into UCD processes, fostering more responsible human–AI collaboration practices (Singu et al. 2026).

## 7. Conclusions

This review provides a multidimensional analysis of the current state and prospects of GenAI chatbots in UCD, and proposes a conceptual framework including cognitive augmentation, collaborative facilitation, and workflow integration. It maps key research themes and emerging trends, showing that GenAI chatbots empower the design process across problem framing and user research, idea generation, prototype development, and iterative evaluation. These chatbots expand designers' capacity for information processing and creativity while facilitating human–AI co-creation through multi-turn interaction, thus enhancing design efficiency and quality. Moreover, GenAI chatbots are evolving from traditional conversational agents into interactive collaborators for generative intelligent design. This perspective offers a useful lens for understanding and expanding human–AI co-creation models.

However, several critical challenges remain, including the reliability of generated content, limited domain-specific knowledge, the dynamics of human–AI co-creative design, and insufficient evaluation frameworks and ethical issues. To optimise the potential of GenAI in design, future research should develop dynamic human–AI feedback mechanisms throughout the UCD lifecycle, strengthen multimodal and domain-specific grounding to improve contextual relevance, and establish systematic evaluation and governance frameworks. Through these efforts, GenAI chatbots could increasingly serve as collaborators for human designers, supporting the vision of human–AI symbiosis in engineering design.

## Notes

1. <https://www.iso.org/standard/21197.html>
2. <https://www.iso.org/standard/77520.html>

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