A Survey of AI Agent and Intelligent Product Design: Integration of AIGC, Computational and Generative Design

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Abstract

The integration of artificial intelligence (AI) into product design represents a transformative shift, leveraging advanced methodologies to enhance creativity, efficiency, and functionality. This survey explores the impact of AI technologies, such as autonomous agents and AI-generated content (AIGC), on design processes, highlighting their role in automating complex tasks and fostering innovation. Key findings indicate that AI significantly enhances user satisfaction through personalized interactions and optimized design solutions, while also democratizing design by enabling non-experts to engage in creative processes. The survey examines the synergy between AI agents and design processes, emphasizing their ability to mediate between design stages and provide real-time feedback. It also addresses the challenges of integrating AI, such as data quality, ethical considerations, and resource limitations, and identifies future research opportunities in enhancing interactivity, robustness, and interdisciplinary collaboration. Case studies in the automotive and architectural sectors illustrate AI's potential to optimize design and manufacturing workflows. As AI continues to evolve, its role in product design is expected to expand, offering new opportunities for creativity and innovation while addressing ethical and resource-related challenges. The survey concludes by emphasizing the importance of ethical frameworks and interdisciplinary collaboration in shaping the future of AI-driven design.

1 Introduction

1.1 Overview of AI in Product Design

The integration of artificial intelligence (AI) into product design signifies a transformative shift, enhancing functionality, aesthetics, and user experiences through the automated generation of multimodal content. This evolution is highlighted by the rise of artificial intelligence-generated content (AIGC), which employs advanced algorithms to streamline design workflows and foster innovation, particularly in augmented reality (AR) applications. As the quality of AI-generated content improves, designers gain unprecedented opportunities to create engaging, interactive experiences while addressing the limitations of existing technologies [1, 2]. AI technologies, including autonomous agents and AIGC, have revolutionized traditional design paradigms by automating complex tasks and reducing reliance on extensive domain expertise. The adoption of Large Language Models (LLMs) exemplifies this shift, aligning AI-driven content creation with human creativity.

AI enhances user satisfaction and engagement through personalized interactions facilitated by AI agent personas that incorporate voice, embodiment, and demographic elements [3]. Additionally, AI-generated content mitigates the constraints of generative AI and procedural content generation, which have traditionally depended on human creators [4]. The application of Explainable AI (XAI) methodologies is crucial for ensuring transparency and comprehensibility in AI-generated content, thereby fostering trust and reliability in AI applications [5]. Furthermore, AI's role in product design

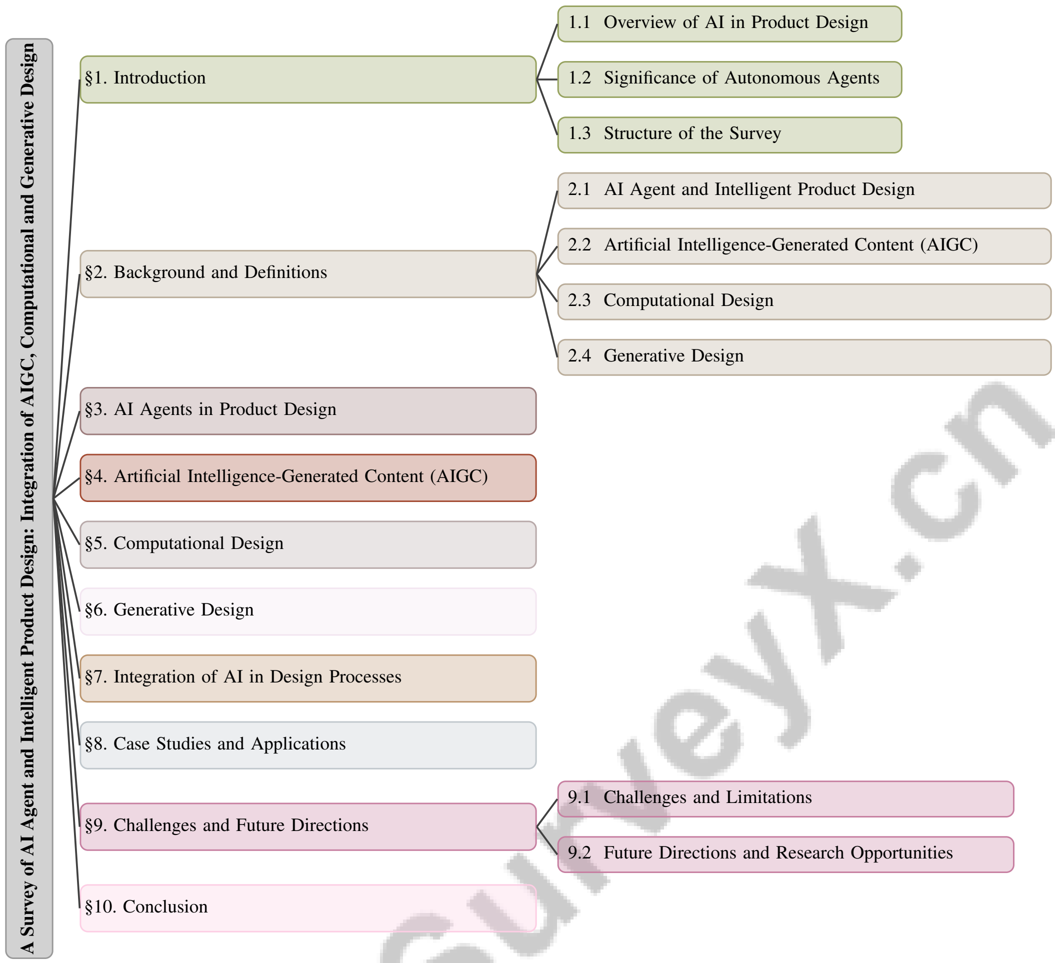

Figure 1: chapter structure

is underscored by its ability to transcend the limitations of human ideation, often restricted by the designer's knowledge [6].

Next-generation digital platforms that incorporate AI technologies represent significant advancements in product design, enabling sophisticated, user-centric solutions [7]. The democratization of innovation in manufacturing, driven by design automation, is a key aspect of AI's impact on product design [8]. Integrating deep learning agents with goal-directed strategies further exemplifies AI's enhancement of design processes [9]. As AI continues to evolve, its influence on product design is expected to broaden, warranting further exploration in subsequent sections of this survey.

AI's potential to assist non-experts in generating narratives about future technological scenarios underscores its role in democratizing design fiction. The development of data-driven intelligent computational design (DICD) provides a systematic framework for applying AI throughout the product design process, addressing existing research gaps. The intersection of AI with bio-inspired design (BID) offers innovative pathways to bridge biological systems and engineering design. AI also addresses complex optimization problems in product development, where traditional iterative methods often face constraints of time and resources [10]. Moreover, the ethical implications of AI systems necessitate a focus on accountability, responsibility, and transparency [11].

1.2 Significance of Autonomous Agents

Autonomous agents play a crucial role in modern design processes by enabling systems to perform tasks with minimal human intervention, thereby enhancing efficiency and innovation. The integration of AI agents not only automates routine tasks but also facilitates complex decision-making, allowing for the exploration of innovative design solutions. Nonetheless, current AI agent architectures face significant challenges in autonomously managing complex tasks, often due to limitations in effective feedback integration [12]. This challenge is compounded by the complexity of designing AI agents that can pursue goals without compromising human welfare [13].

Trust is essential for the adoption and efficacy of autonomous agents, especially those based on LLMs. The dynamics of trust in these AI systems differ from traditional automation methods, necessitating a focused approach to building and maintaining user trust [14]. Developing mechanisms for AI agents to generate accurate explanations for users is vital for enhancing trust and understanding [15]. In cooperative human-AI interactions, employing mental models can significantly improve explainability, fostering effective collaboration [16].

The perception of AI agents is significantly influenced by the metaphors used to describe them, which shape user expectations and evaluations. Metaphors related to warmth and competence can profoundly affect how users perceive the capabilities and intentions of AI agents [17]. Addressing negative preconceptions is crucial for the broader adoption of AI technologies, necessitating innovative methods to enhance user perceptions and trust in AI systems [18].

Integrating AI agents, particularly LLMs, into robotic systems presents additional challenges in ensuring reliable and safe operations in dynamic environments [6]. Furthermore, the 'chicken-and-egg' problem, where designers and engineers must understand each other's domains to create effective AI experiences, remains a significant obstacle in co-creating AI-driven design processes [9]. Addressing these challenges is essential for realizing the full potential of autonomous agents in transforming modern design processes.

1.3 Structure of the Survey

This survey is systematically organized to provide a comprehensive examination of the integration of AI technologies within product design. The introductory section discusses the significance of AI agents and intelligent product design, emphasizing the transformative roles of autonomous agents, AIGC, and algorithm-driven design processes. Following the introduction, Section 2 delves into background and definitions, offering detailed explanations of core concepts such as AI Agent, Intelligent Product Design, AIGC, computational design, and generative design, thereby establishing a foundational understanding for subsequent discussions.

Section 3 focuses on AI agents in product design, exploring their capabilities in automating and optimizing design processes to enhance functionality, aesthetics, and user experience. This is followed by a dedicated analysis of AIGC in Section 4, critically examining its impact on creativity and innovation in design. Section 5 shifts to computational design, discussing methodologies and techniques for creating complex and optimized design solutions.

In Section 6, principles and applications of generative design are thoroughly examined, emphasizing how AI utilizes generative techniques—such as generative pre-trained transformers (GPT)—to explore diverse design possibilities. This includes a discussion on AI's role in generating innovative design concepts, particularly in multimodal media content creation for environments like augmented reality, enhancing the design process by providing a structured framework for evaluating technology adoption [19, 2]. Section 7 discusses the integration of AI technologies into design processes, exploring the synergy among AI agents, AIGC, computational design, and generative design, while addressing the benefits and challenges of such integration.

The survey further includes Section 8, presenting case studies and applications that showcase successful implementations of AI in intelligent product design across various industries, providing practical insights into the real-world impact of AI-driven design methodologies. Section 9 identifies challenges and future directions in the field, discussing technical, ethical, and resource-related challenges while highlighting emerging trends and potential research opportunities.

Finally, the paper concludes with a summary of key points discussed, reflecting on the impact of AI technologies on product design and the potential for future advancements in this rapidly evolving field. This structured approach facilitates an in-depth examination of AI's contributions to product design, yielding critical insights for researchers and practitioners. By leveraging AI technologies, such as BERT-based agents, this methodology enhances the efficiency of evidence synthesis processes and highlights the transformative potential of AI in streamlining workflows and improving decision-

AI-generated, for reference only.

making across various domains, including global development and content generation [20, 1].The following sections are organized as shown in Figure 1.

2 Background and Definitions

2.1 AI Agent and Intelligent Product Design

AI agents are advanced computational entities that autonomously execute tasks, optimizing actions across various domains, and significantly contributing to intelligent product design. They enable mixed-initiative processes that integrate human and AI inputs, achieving optimal design outcomes while balancing speed with accuracy, thus mitigating existential risks [21, 13]. These agents enhance user experiences by facilitating seamless context sharing and addressing fragmentation in conversational AI [22]. Transparency and explainability are crucial for building user trust, as AI agents must provide comprehensible recommendations and decisions [23]. Their application in optimizing neural network architectures demonstrates their ability to refine computational methods, enhancing both creative and functional design elements [24]. Additionally, AI agents streamline the conceptual design phase by automating processes traditionally reliant on extensive CAD models and CAE results, significantly reducing prediction costs [25].

AI agents democratize the design process, allowing non-experts to engage in activities like furniture creation without specialized skills [26], and platforms enabling non-technical users to create intelligent tutors exemplify this democratization [27]. Furthermore, AI agents recommend optimal conditions for complex processes, such as chemical synthesis, where traditional AI systems often struggle with generalization [28]. Their integration into intelligent product design is further enriched by their capacity to mediate thought processes in environments requiring parametric design tools and algorithmic logic, which often necessitate abstract thinking [29]. However, challenges like unpredictable AI behavior and alignment failures necessitate robust governance mechanisms as these systems become integral to critical infrastructures [30]. Ethical considerations are paramount, emphasizing the need for responsible AI frameworks that incorporate ethical reasoning and stakeholder involvement in decision-making. Additionally, integrating AI agents into economic models better reflects their impact on user decision-making, underscoring their role in developing Smart Product-Service Systems (Smart PSS) tailored to personalized user needs.

2.2 Artificial Intelligence-Generated Content (AIGC)

Artificial Intelligence-Generated Content (AIGC) involves creating digital media, including text, images, audio, and video, through advanced AI technologies. It significantly boosts creativity and innovation in design processes, enabling content generation that aligns with market demands and allowing designers to explore a wide range of possibilities. The incorporation of user-generated data into Smart Product-Service Systems (Smart PSS) exemplifies AIGC's role in fostering personalized and adaptive design solutions [31]. Platforms like Civitai highlight AIGC's dual nature, showcasing vibrant artistic expression alongside risks such as deepfakes and abusive content [32]. Concept-based Controllable Generation (CoCoG) further illustrates AIGC's potential by integrating cognitive science with AI, enabling the generation of visual stimuli based on human concept representations [32].

A survey of AIGC development in China underscores its strategic importance in shaping national and international design landscapes, highlighting global trends and competitiveness [33]. Despite its transformative potential, AIGC faces challenges related to data quality, privacy, and misuse. Research advocates for watermarking techniques to prevent misinformation and intellectual property theft, thereby enhancing the reliability of AI-generated content [33].

2.3 Computational Design

Computational design represents a paradigm shift in product development, utilizing advanced algorithmic processes to generate optimized and innovative design solutions. This approach incorporates methodologies such as deep learning algorithms, central to data-driven intelligent computational design (DICD), allowing for the automation and enhancement of design processes [34]. Its significance is particularly evident in addressing complex design challenges through techniques like the Generative Shape Modeling Algorithm, enabling non-experts to create 3D shapes by specifying functional requirements [35]. Frameworks like Design-Informed Generative Modelling (DIGM) emphasize

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topology, layout, and size optimization in generating CAD models that satisfy structural integrity requirements, reducing the time and resources needed for design iteration [36]. Generative design techniques in systems like the Dynamic Visual Identity Generation System (DVI-GS) further illustrate how computational design can produce bespoke visual outputs aligned with desired aesthetics [37].

The integration of deep learning techniques in additive manufacturing showcases computational design's role in process modeling, optimization, and monitoring, leading to more efficient design solutions [38]. The Layered Hierarchy Architecture exemplifies how computational design can merge AI decision-making with instinctual safety mechanisms, enhancing reliability and functionality [6]. Moreover, computational design methodologies address traditional workflow limitations in molecular property prediction and generative design by retrieving critical information for material design tasks, thereby enhancing material innovation capabilities [39]. The exploration of designs through algorithms, as discussed in generative design literature, enables rapid development of innovative solutions and expands design possibilities [10].

2.4 Generative Design

Generative design is an advanced computational methodology employing algorithmic processes to autonomously explore a vast array of design possibilities while adhering to predefined constraints and objectives. This approach facilitates the creation of innovative and efficient design solutions by systematically navigating the design space, allowing designers to produce diverse outcomes that meet specific requirements [10]. A key feature is its ability to generate multiple design alternatives, often outperforming traditional human-engineered solutions by uncovering non-intuitive results [10]. The integration of generative design in additive manufacturing is exemplified by methodologies that create high-performing space-frame solutions, streamlining the design process and enhancing innovative applications [40]. This is further advanced by frameworks that incorporate human revision edits into multimodal generative models, refining outputs based on feedback and improving quality and applicability [41].

Generative design tools significantly influence the design process, enabling broader exploration of possibilities and fostering creativity, impacting the subjective aspects of design [42]. The ability to generate novel content positions generative AI as an agent within economic models, akin to a human consultant, illustrating its potential contribution to economic decision-making [43]. Applications of generative design span various domains, including civil engineering, where challenges persist in producing valid floor plans that meet specific constraints [44]. In landscape architecture, AI-aided design processes prioritize topological relationships over traditional parameters, facilitating innovative green space designs [45].

Despite its transformative potential, generative design faces challenges, such as the generation of high-quality 3D models from textual descriptions, complicated by the unique properties of 3D data and limitations of existing methods [46]. As research progresses, generative design is poised to drive significant advancements in creative solution development, expanding the boundaries of design innovation and offering novel pathways for exploring design possibilities.

3 AI Agents in Product Design

The integration of AI agents is revolutionizing product design by streamlining processes, enhancing creativity, and fostering innovative solutions. This section examines the diverse impacts of AI agents, with a focus on automated design optimization, showcasing methodologies that refine design outcomes. Figure 2 illustrates the hierarchical structure of AI agents in product design, highlighting key categories such as Automated Design Optimization and User Experience and Interaction. Each category is further divided into methodologies, frameworks, and user engagement strategies, emphasizing the integration of AI in streamlining design processes and enhancing user interactions. This visual representation not only complements the textual analysis but also provides a structured overview of the various dimensions through which AI agents influence product design.

3.1 Automated Design Optimization

AI agents have transformed design optimization by automating complex tasks, boosting efficiency, and fostering creativity in product development. Key methodologies like reinforcement learning and

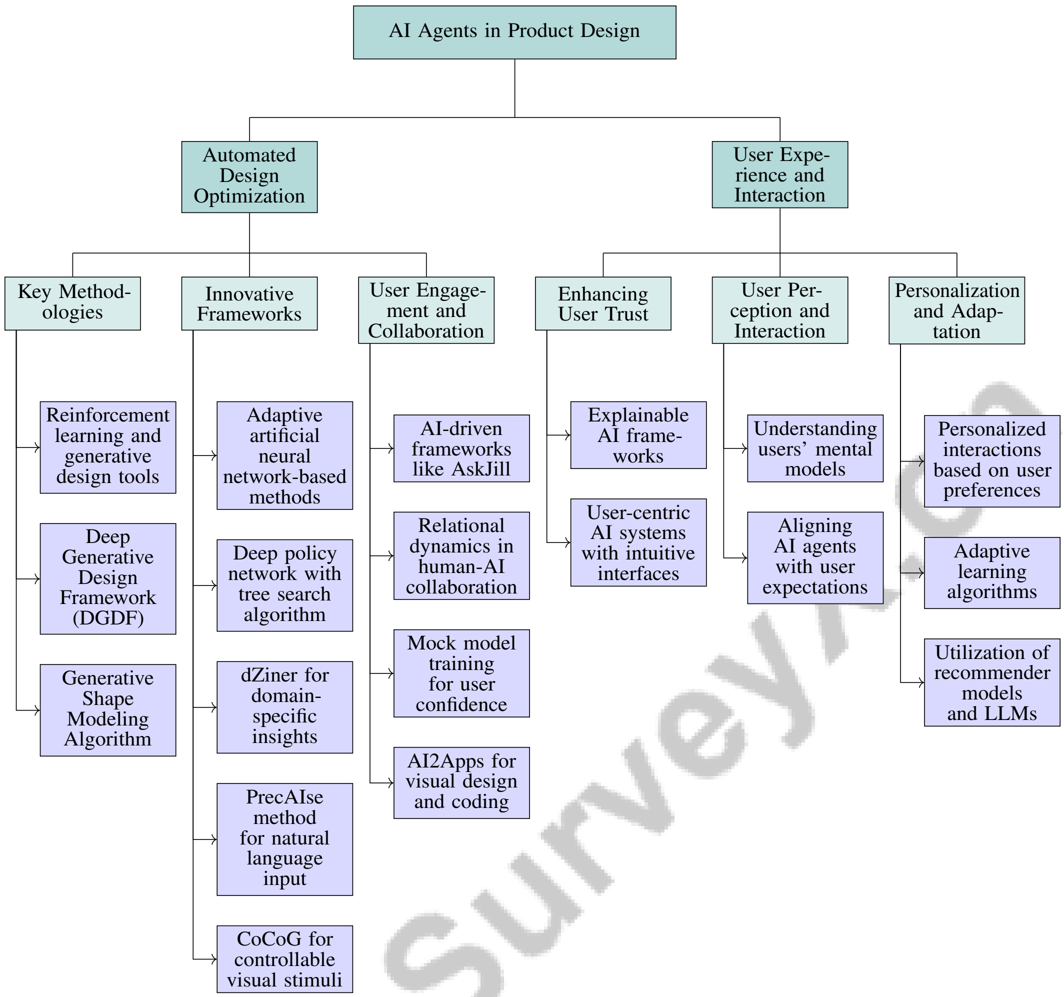


Figure 2: This figure illustrates the hierarchical structure of AI agents in product design, highlighting key categories such as Automated Design Optimization and User Experience and Interaction. Each category is further divided into methodologies, frameworks, and user engagement strategies, emphasizing the integration of AI in streamlining design processes and enhancing user interactions.

generative design tools are crucial in refining workflows. The Deep Generative Design Framework (DGDF) exemplifies this evolution, merging topology optimization with generative models to create and assess diverse designs based on engineering and aesthetic criteria [47]. The Generative Shape Modeling Algorithm further advances automated design optimization by enabling the creation of complex geometries from high-level functional specifications [35].

As illustrated in Figure 3, the hierarchical structure of automated design optimization highlights key methodologies, frameworks, and tools, as well as user engagement strategies. This figure categorizes the main approaches and innovations in AI-driven design processes, providing a visual representation that complements the textual analysis presented herein.

Adaptive artificial neural network-based methods iteratively improve design candidates, dynamically adjusting the design space based on previous outcomes, thus minimizing the need for extensive training data [48]. Furthermore, the integration of a deep policy network with a novel tree search algorithm allows AI agents to discover high-performing generative strategies without prior data reliance, enhancing automation in design processes [49].

Frameworks such as dZiner leverage domain-specific insights and surrogate models to automate design processes, enabling the generation and evaluation of new candidate molecules based on user-defined properties and constraints [50]. The PrecAIse method enhances accessibility and user engagement by allowing users to input natural language descriptions of use cases, thus streamlining design processes [8]. CoCoG optimizes design through controllable visual stimuli generation, aligning AI-generated images with human cognitive processes [51].

AI-driven frameworks like AskJill enhance user engagement through sustained dialogues, improving decision-making and design communication. The relational dynamics of human-AI collaboration, as highlighted in creative writing frameworks, emphasize the importance of interactions beyond performance improvements, fostering a deeper understanding of collaborative processes [52]. Mock model training, where users label training data for AI agents, bolsters user confidence and engagement, optimizing design processes through enhanced system reliability [18].

AI2Apps represents an innovative platform that enables developers to visually design and code AI agent applications efficiently, contributing to the optimization of design processes by simplifying the development and deployment of AI-driven solutions [7].

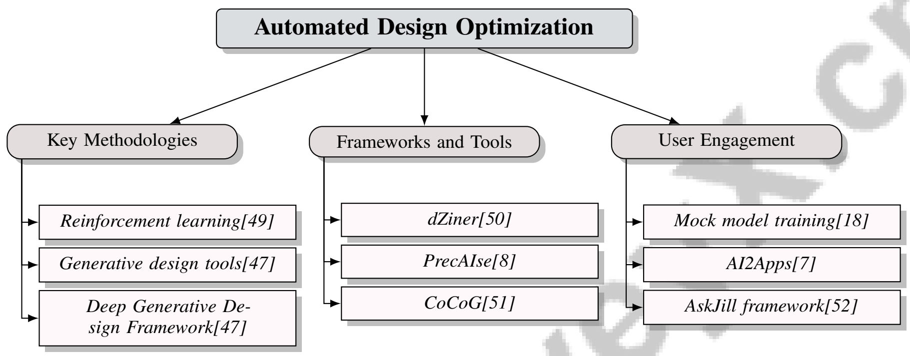


Figure 3: This figure illustrates the hierarchical structure of automated design optimization, highlighting key methodologies, frameworks, and tools, as well as user engagement strategies. It categorizes the main approaches and innovations in AI-driven design processes.

3.2 User Experience and Interaction

AI agents substantially enhance user experience and interaction in product design by addressing challenges such as high learning costs, limited effectiveness, and trust issues associated with the 'black box' nature of Artificial Intelligence-Generated Content (AIGC) processes [53]. By incorporating explainable AI frameworks, these agents promote transparent interactions, boosting user trust and engagement. User-centric AI systems prioritize intuitive interfaces that reduce cognitive load, facilitating navigation and interaction with complex design tools.

Understanding users' mental models of AI agents is crucial for improving team performance and trust, as these models offer insights into user perceptions and interactions with AI systems [54]. Aligning AI agents with user expectations enables designers to foster seamless and effective interactions, especially in collaborative design environments where human intuition and AI-generated insights converge to produce innovative, user-centric solutions.

Furthermore, AI agents personalize interactions based on user preferences and behaviors, utilizing advanced adaptive learning algorithms to dynamically adjust responses and recommendations based on user behavior data and real-time feedback. This personalization ensures that interactions remain relevant and engaging, leveraging both recommender models and large language models (LLMs) to enhance user satisfaction [55, 56, 24, 57, 1]. By harnessing data-driven insights, AI agents can anticipate user needs and provide proactive support, thereby enriching the overall design experience.

4 Artificial Intelligence-Generated Content (AIGC)

4.1 AI-Driven Content Creation

AI-driven content creation is reshaping design practices by integrating advanced methodologies that enhance innovation and expand design possibilities. The use of Artificial Intelligence-Generated Content (AIGC) within design frameworks facilitates a deeper understanding of AI behaviors, crucial

AI-generated, for reference only.

for effective collaboration between AI and human designers [4]. This synergy is essential for leveraging the strengths of both entities. The transformative potential of AIGC across industries necessitates regulatory frameworks to ensure its ethical deployment [33]. By automating content creation, AI empowers designers to explore new creative avenues, democratizing design tools and enabling novice users to engage in complex tasks, thereby enhancing accessibility and inclusivity.

AI-driven content creation also significantly enhances user engagement by generating personalized, contextually relevant outputs tailored to individual preferences. This not only enriches the user experience but also utilizes sophisticated algorithms and large-scale pretrained models to produce high-quality results. The integration of explainable AI methodologies improves user interaction and addresses challenges associated with AIGC tools, resulting in a stronger user connection to the content and increased participation in digital environments [58, 53, 1]. The adoption of AI in content creation streamlines design processes and introduces innovative methodologies that expand traditional paradigms, positioning AI as a central player in the future of design.

4.2 Impact on Creativity and Innovation

Benchmark	Size	Domain	Task Format	Metric
AGIQA-1K[59]	1,080	Image Quality Assessment	Quality Evaluation	SRoCC, PLCC
AGT[60]	102	Human-AI Interaction	Turing Test	Confusion Rate
AIGIQA-20K[61]	420,000	Image Quality Assessment	Quality Assessment	SRoCC, PLCC
AIGCIQA2023+[62]	2,400	Image Quality Assessment	Image Quality Assessment	MOS, VQA acc
AIGCOIQA2024[63]	300	Image Quality Assessment	Quality Assessment	SRCC, PLCC
Meta-VAE[64]	20,000	Industrial Design	System Generation	Contact Constraint Absolute Error, Performance Measure
AIGC-VQA[65]	2,808	Video Quality Assessment	Quality Assessment	SRCC, PLCC

Table 1: This table presents a comprehensive overview of various benchmarks used in the assessment of AI-generated content, highlighting their size, domain, task format, and evaluation metrics. These benchmarks span different applications such as image and video quality assessment, human-AI interaction, and industrial design, providing a diverse set of metrics like SRoCC, PLCC, MOS, and others. The information serves to illustrate the breadth of methodologies employed in evaluating AI-generated content across multiple domains.

AIGC significantly enhances creativity and innovation in design by providing tools and methodologies that transcend traditional limitations. As illustrated in Figure 4, the impact of AI-Generated Content (AIGC) on creativity and innovation encompasses generative design tools, advanced AI techniques, and the associated challenges and solutions. Generative design tools are effective in boosting creativity and efficiency during the conceptual phase, enabling designers to explore a wide range of possibilities [66]. These tools facilitate the discovery of innovative solutions that may not be apparent through conventional methods. Advanced AI techniques, such as Generative Adversarial Networks (GANs), exemplified by CreativeGAN, automate creativity in design synthesis, generating unique designs with novel features that challenge traditional paradigms [67]. Interactive platforms like SketchDreamer democratize creativity by allowing users to create sketches through text inputs and initial drawings, enhancing accessibility to design innovation [68].

Despite these advancements, challenges persist in evaluating the quality of AI-generated content. Table 1 provides a detailed overview of the benchmarks utilized in evaluating the quality and effectiveness of AI-generated content, which are crucial for understanding the impact of AIGC on creativity and innovation. Current Image Quality Assessment (IQA) models often inadequately assess the perceptual quality of AIGC, necessitating improved evaluation frameworks [59]. The IPCE method offers a promising approach by aligning assessments with human perception, thereby enhancing the creative potential of design processes [69]. Additionally, the significant energy consumption associated with diffusion model-based AIGC, particularly during denoising, poses a challenge for efficient execution on mobile devices [70]. Addressing these energy constraints is essential for broadening AIGC's applicability across platforms.

AIGC's role in stimulating creativity and innovation is underscored by its potential for economic growth and the need to address technical and ethical challenges [71]. As research progresses, overcoming obstacles such as evaluation frameworks, energy consumption, and the necessity for diverse datasets will be crucial for maximizing AIGC's impact on the future of design. Moreover, AI agents designed with higher levels of agreeableness are perceived as more human-like, enhancing user interaction and acceptance of AIGC [60]. Understanding sentiment towards AI-generated content across different communities will be essential for promoting acceptance and participation as AIGC evolves [58].

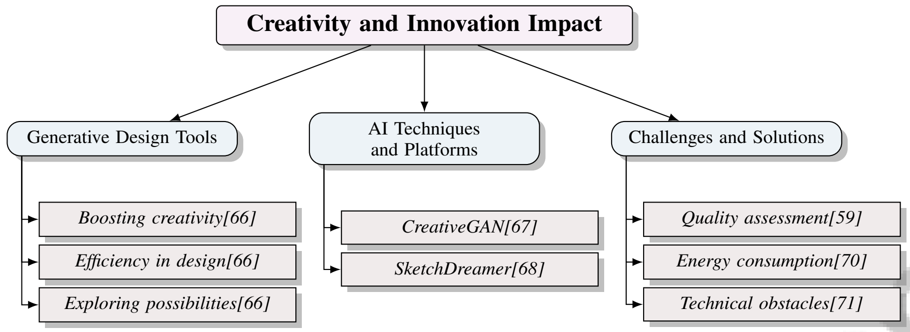


Figure 4: This figure illustrates the impact of AI-Generated Content (AIGC) on creativity and innovation, highlighting generative design tools, advanced AI techniques, and associated challenges and solutions.

5 Computational Design

Category	Feature	Method
Techniques and Methodologies	Generative and Iterative Processes Hybrid Systems	MOBO[72], DCIF[73] AJ[23]
Optimization and Design Automation	Data-Driven Enhancement	KG-CK[31]

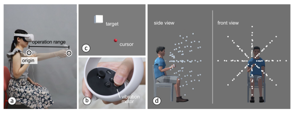
Table 2: This table provides a comprehensive summary of various computational design methodologies, highlighting key techniques and optimization strategies. It categorizes the methods based on their functional areas, such as generative and iterative processes, hybrid systems, and data-driven enhancements, demonstrating the diverse approaches employed in advancing computational design.

Recent advancements in computational design have been driven by the need for innovative solutions and increased efficiency. Table 2 presents a detailed overview of the main techniques and methodologies utilized in computational design, illustrating the innovative approaches and optimization strategies that drive advancements in this field. Additionally, Table 3 presents a comparative analysis of key computational design methodologies, illustrating their unique optimization techniques, collaboration models, and application areas within the evolving field of computational design. This section delves into the diverse methodologies of computational design and its implications across various domains, focusing on the techniques that define this evolving discipline.

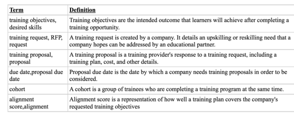
5.1 Techniques and Methodologies

Computational design techniques utilize a range of methodologies aimed at optimizing design outcomes. The Deep Concept Identification Framework (DCIF) exemplifies the use of generative design techniques, organizing diverse design alternatives in a latent space through representation learning to facilitate solution optimization [73]. The Co-Creation Process Model for AI Experiences (AIX Model) enhances design by structuring collaborative sessions between designers and engineers, highlighting the importance of interdisciplinary collaboration in AI-driven design [9]. The KG-aided C-K approach integrates Knowledge Graphs and the Concept-Knowledge model, supporting the development of Smart Product-Service Systems (Smart PSS) and improving design quality and efficiency [31].

These methodologies demonstrate the transformative potential of computational design, integrating advanced techniques such as Generative Design Approach (GDA) and AI to explore extensive design solution spaces. This integration enhances the quality and diversity of outputs and provides innovative pathways for optimizing solutions in fields like architecture and product development. Iterative processes and data-driven decision-making empower designers to navigate complex constraints, fostering innovation in design concepts [74, 19, 75]. As research progresses, these techniques are poised to significantly influence intelligent product development.

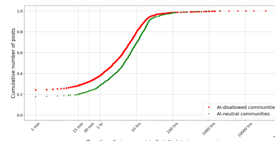


(a) Virtual Reality Interaction with a Vibration Motor[72]



Term	Definition
training objectives, desired skills	Training objectives are the intended outcome that learners will achieve after completing a training opportunity.
training request, RFP, request	A training request is created by a company. It details an upskilling or reskilling need that a company hopes can be addressed by an educational partner.
training proposal, proposal	A training proposal is a training provider's response to a training request, including a training plan, cost, and other details.
due date,proposal due date	Proposal due date is the date by which a company needs training proposals in order to be considered.
cohort	A cohort is a group of trainees who are completing a training program at the same time.
alignment score,alignment	Alignment score is a representation of how well a training plan covers the company's requested training objectives

(b) Training Objectives and Related Terms[23]



(c) Cumulative number of posts in AI-disallowed and AI-neutral communities over time[58]

Figure 5: Examples of Techniques and Methodologies

As shown in Figure 5, innovative techniques and methodologies are crucial in advancing computational design. The example of "Virtual Reality Interaction with a Vibration Motor" illustrates an immersive VR setup enhancing user experience through tactile feedback. "Training Objectives and Related Terms" provides an overview of essential terminology, emphasizing the importance of clear definitions in effective training programs. "Cumulative number of posts in AI-disallowed and AI-neutral communities over time" offers insights into AI discourse across online platforms, showcasing the multifaceted nature of computational design in interactive technologies, educational frameworks, and data-driven analysis [72, 23, 58].

5.2 Optimization and Design Automation

Optimization and automation in design processes are significantly enhanced through computational design, employing advanced algorithms to streamline efficiency and foster innovation. The KG-CK approach enables automatic knowledge retrieval and integration, optimizing design workflows and improving decision-making [31]. Generative design methodologies, such as those in Autodesk Fusion 360, focus on iterative design generation to minimize weight and maximize performance, showcasing improvements in efficiency and output quality. The Generative Design Approach (GDA) transforms design problems into configuration challenges, allowing exploration of extensive solution spaces and enhancing decision-making capabilities with AI [19, 35, 75, 74, 73].

The Active Generative Design (AGD) method enhances material discovery by integrating active learning techniques to improve property prediction models, broadening material exploration beyond existing databases and enhancing design efficiency [19, 76, 75, 74, 77]. The one-shot generation mechanism proposed by Cang et al. advances AIGC, utilizing large pretrained models to efficiently produce high-quality content, meeting the demand for scalable solutions and contributing to generative AI evolution [78, 1]. This approach enables adaptive learning from true solutions, improving generalization in generating optimal topologies.

The SLDA framework exemplifies design process automation, enabling agents to learn design strategies from scratch using self-generated data. Combining deep learning and tree search algorithms, this framework enhances automation and creativity in design, allowing zero-shot generalization across unseen conditions. It integrates topology optimization and generative models, producing diverse and optimized designs for various engineering challenges [49, 47].

Feature	Deep Concept Identification Framework (DCIF)	Co-Creation Process Model for AI Experiences (AIX Model)	KG-aided C-K approach
Optimization Technique	Generative Design	Not Specified	Knowledge Integration
Collaboration Model	Not Specified	Interdisciplinary Collaboration	Not Specified
Application Area	Solution Optimization	Ai-driven Design	Smart Pss

Table 3: The table provides a comparative analysis of three distinct computational design methodologies: the Deep Concept Identification Framework (DCIF), the Co-Creation Process Model for AI Experiences (AIX Model), and the KG-aided C-K approach. It highlights the differences in optimization techniques, collaboration models, and application areas, offering insights into their respective contributions to solution optimization, AI-driven design, and smart Product-Service Systems.

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6 Generative Design

6.1 Principles of Generative Design

Generative design represents a cutting-edge computational approach that leverages sophisticated algorithms to autonomously explore a multitude of design possibilities while adhering to predefined constraints and objectives. This iterative methodology facilitates continuous refinement through machine learning techniques, such as Variational Autoencoders (VAE) and surrogate modeling, in conjunction with evolutionary algorithms, proving particularly effective in applications like 3D printing [79]. A central characteristic of generative design is the dynamic adjustment of design parameters via reinforcement learning, enabling the creation of diverse designs based on reference models and expanding the solution space [80]. Long Language Models (LLMs) further enrich this process by providing context-aware creative suggestions, enhancing the effectiveness of design tools [81].

Generative design frameworks excel in optimizing structural elements, such as the topology and reinforcement of concrete beams, by segmenting these components and applying advanced algorithms to minimize material usage while ensuring structural integrity [82]. Innovations such as converting topology optimization results into computationally efficient skeletonized representations significantly enhance the additive manufacturing design process [40]. Spatial stochastic search techniques, integrated with recommender systems like the V-Dream approach, allow for dynamic reorganization of the solution space based on user preferences, promoting adaptability and creativity [83]. Design Strategy Networks (DSN) employ a hierarchical structure to focus on relevant design regions, sampling feasible actions to improve prediction accuracy and broaden exploration [84].

The systematic categorization of design alternatives, embedding topology optimization results into latent spaces followed by clustering techniques, underscores generative design's potential for refining and optimizing solutions [73]. Generative design tools also enable dynamic visual identity generation through Assisted and Automatic methods, fostering flexibility and creativity in the design process [37].

6.2 Applications in Product Development

Generative design has become a transformative force in product development, offering innovative solutions across various domains through advanced computational techniques. Notably, in bicycle design, CreativeGAN generates unique designs by leveraging a dataset of existing models, creating novel variations that enhance aesthetics and functionality [67]. In immersive exploration and spatial understanding, the V-Dream system exemplifies generative design by enriching user experiences in virtual environments, enhancing spatial understanding and informing design decisions for more creative outcomes [83].

In landscape architecture, the Layout2Rendering system demonstrates the impact of generative design by rapidly generating and analyzing landscape models, allowing efficient exploration of various scenarios and streamlining the creation of innovative and sustainable green spaces [45]. In structural engineering, integrating topology optimization with generative models marks a significant advancement, enabling the iterative generation of diverse design alternatives from limited initial designs, improving both aesthetic quality and engineering performance [47].

Generative design reshapes product development by employing advanced algorithms and artificial intelligence to automate the exploration of extensive design solution spaces. This capability allows teams to rapidly evaluate and optimize designs based on various parameters, enhancing creativity and efficiency while significantly improving performance across industries. The generation of optimal designs that consider stress analysis and load paths leads to superior product outcomes [85, 77, 75, 10]. As research and technology continue to progress, generative design is poised to play an increasingly critical role in shaping the future of product development.

7 Integration of AI in Design Processes

The integration of artificial intelligence (AI) in design processes signifies a major shift in intelligent product design by redefining traditional methods and introducing new paradigms that enhance creativity, efficiency, and collaboration. This integration fosters synergy between AI agents and design processes, particularly in Mixed-Initiative Co-Creative (MI-CC) systems. Adaptive AI agents, which learn from human creators, enhance creativity and satisfaction, leading to innovative outcomes. Research highlights AI's role in generating novel outputs and promoting collaborative interactions, enriching the design environment and enabling meaningful creative experiences [58, 56, 86, 52].

7.1 Synergy between AI Agents and Design Processes

The integration of AI agents into design processes significantly advances intelligent product design by creating a collaborative environment that boosts creativity, efficiency, and innovation. Studies demonstrate how AI assistance in creative tasks, such as design fiction and evidence synthesis, enables deeper engagement with unexpected AI-generated content, supports participatory approaches, and reduces manual effort in literature screening. The benefits of proactive AI roles in MI-CC systems are evident in improved user satisfaction and collaborative outcomes, underscoring AI's transformative potential in enriching the design landscape and fostering interdisciplinary collaboration [9, 56, 87, 52, 20]. AI agents serve as pivotal facilitators, bridging human intuition with computational precision, equipped with advanced learning capabilities to autonomously execute complex tasks and optimize design outcomes through iterative processes.

A crucial aspect of this synergy is AI agents' ability to mediate between different design stages, offering insights and recommendations aligned with specific design objectives. AI-driven platforms like AI2Apps exemplify this mediation, providing a visual interface that allows designers to leverage AI capabilities without requiring extensive technical expertise [7]. Additionally, AI agents enhance the exploration of design possibilities by swiftly analyzing and adapting to new information, thereby improving the iterative nature of design [29]. This adaptability is essential in dynamic environments where design requirements evolve, allowing AI agents to provide real-time feedback that aligns with user preferences and market trends.

The collaborative dynamics between AI agents and design processes are further enriched by integrating explainable AI frameworks, which enhance transparency and trust by offering clear explanations of AI-driven decisions [15]. This transparency is vital for fostering user trust and ensuring AI agents are perceived as reliable partners in the design process. Furthermore, AI agents optimize user experience by personalizing interactions based on user behavior and preferences, enhancing engagement and satisfaction [54].

7.2 Integration with Design Tools

The integration of AI technologies with existing design tools represents a significant advancement in intelligent product design, facilitating enhanced creativity, efficiency, and innovation. AI technologies are increasingly embedded into design tools, enabling designers to leverage computational power and advanced algorithms without extensive technical expertise. Platforms such as AI2Apps provide a visual interface for the development and deployment of AI applications, streamlining the process for designers and developers [7].

A key aspect of this integration is the enhancement of design workflows through AI-driven automation and optimization. AI technologies automate routine design tasks, allowing designers to focus on more creative and strategic aspects of the design process. Generative design tools exemplify this capability, enabling designers to explore a wide range of design possibilities while optimizing for criteria such as material usage, structural integrity, and aesthetic appeal [47]. This capability accelerates the design process and expands designers' creative potential.

Moreover, AI technologies integrated into design tools facilitate real-time feedback and iterative refinement of design solutions. By analyzing user interactions and design outcomes, AI systems provide personalized recommendations and adjustments, ensuring alignment with user preferences and market trends [54]. This adaptability is crucial in dynamic design environments where requirements are constantly evolving.

The integration of AI into design tools also enhances collaboration among multidisciplinary teams. AI systems mediate between different design stages, offering insights and recommendations aligned with specific design objectives. This collaborative dynamic is particularly evident in co-creation platforms that enable designers and engineers to work together seamlessly, refining and optimizing design solutions through AI capabilities [9].

Furthermore, incorporating explainable AI frameworks into design tools enhances transparency and trust by providing clear explanations of AI-driven decisions [15]. This transparency is essential for fostering user trust and ensuring AI technologies are perceived as reliable partners in the design process.

8 Case Studies and Applications

8.1 Automotive Industry Applications

The automotive industry demonstrates the transformative influence of artificial intelligence (AI) in refining design and manufacturing processes. A pivotal innovation is the Generative Design for Additive Manufacturing (G-DfAM) method, which optimizes workflows by producing complex, lightweight, and structurally efficient geometries. This ensures components meet stringent performance and safety standards while reducing material usage [88]. Beyond design optimization, AI enhances communication and connectivity systems, as illustrated in studies like 'Capacity Maximization for Non-Parallel Transceiver' and 'EDoF Maximization for Various Shapes of Transceiver'. These case studies highlight AI's role in optimizing capacity performance and effective degrees of freedom (EDoF) in XL-MIMO systems, showcasing its critical contribution to advancing automotive communication networks [89]. By employing AI agents for configuration analysis, the automotive sector can develop more efficient and reliable communication systems, crucial for autonomous and connected vehicles.

AI integration in the automotive industry highlights its potential to boost design innovation, manufacturing efficiency, and communication processes. Advanced AI technologies, including AI-generated content (AIGC), streamline content creation and optimize workflows. The synergy between AI and intelligent manufacturing systems is revolutionizing production models, fostering more adaptable manufacturing environments. This transformation enhances operational performance and meets the digital economy's demands [2, 90, 1]. As AI evolves, its applications in the automotive sector are expected to expand, driving further innovation and efficiency in vehicle development and production.

8.2 Generative Design in Architecture

Generative design significantly influences architecture by enabling the exploration of diverse design possibilities and optimizing building performance through advanced computational techniques. In architectural projects, these methodologies facilitate the creation of innovative structures that fulfill aesthetic and functional requirements. A notable example is the use of generative design in complex urban environments, where algorithms optimize spatial configurations, enhance energy efficiency, and promote sustainability [45].

AI-driven generative design tools empower architects to dynamically explore design alternatives, accelerating the design process and expanding creative potential by revealing non-intuitive solutions often overlooked in traditional methods [10]. This approach is exemplified in adaptive façade systems, where algorithms optimize element arrangements to improve natural lighting and thermal performance [40].

Moreover, generative design techniques address urban density and land use challenges. By employing spatial stochastic search methods, architects can efficiently evaluate various urban layouts, maximizing available space while ensuring livability and accessibility [83]. These capabilities are particularly valuable for sustainable urban development, balancing environmental, social, and economic considerations. Additionally, generative design optimizes structural elements, such as beams and columns, by minimizing material usage while maintaining structural integrity. This optimization is crucial for reducing construction costs and environmental impact, positioning generative design as a vital tool for sustainable architectural practices [82].

9 Challenges and Future Directions

9.1 Challenges and Limitations

AI-driven design faces significant challenges across technical, ethical, and resource domains. A primary technical issue is the lack of high-quality training data, particularly for 3D models, which hampers output fidelity and realism, complicating generative processes' consistency and controllability [33]. Additionally, managing complex design scripts and errors in generated plans due to inadequate semantic understanding further complicates generative design [44]. Variability in crowd responses and data quality from crowd-sourced data further complicate decision-making [91].

Ethically, AI systems' potential to generate illegal or harmful content raises concerns for legal governance and ethical oversight [32]. The absence of standardized ethical guidelines and the complexity of integrating ethical considerations into AI design challenge responsible AI development [11]. Stakeholder resistance to unfamiliar generative designs can also impede AI methodology acceptance [10].

Resource challenges include the availability and quality of data necessary for effective AI model training, emphasizing the need for comprehensive datasets [33]. The unpredictability of AI-generated candidates in active learning-based generative design can lead to inefficient computational resource use. Additionally, a shortage of skilled professionals and funding for AIGC companies limits innovation potential [33].

Addressing these challenges requires efforts to enhance computational efficiency, ensure ethical content generation, and develop resource-efficient design tools. Overcoming these limitations is vital for leveraging AI's capabilities in design, improving evidence synthesis for global development, generating high-quality content through AIGC, and facilitating cross-domain knowledge discovery with multi-AI agent systems. Such advancements are crucial for fostering innovation across various fields and enabling timely, evidence-based decision-making [87, 20, 1].

9.2 Future Directions and Research Opportunities

The future of AI-driven design is rich with opportunities emphasizing interactivity, robustness, and interdisciplinary collaboration. Key areas for exploration include refining generative design frameworks to incorporate 3D designs and voxel data, and developing recommendation systems to assist designers in optimal design selection based on preferences [47]. Automating the generative process with physics simulations and extending recurrent neural networks (RNNs) to generate gears with continuous design parameters also present exciting research avenues [92].

Enhancing AI capabilities involves developing robust methods for real-time adaptation of AI explanations based on user feedback, improving user-AI interaction [16]. Additionally, enhancing model generalizability across different visual domains, particularly within the CoCoG framework, is essential for advancing AI-driven design [32].

In manufacturable designs, future research should focus on extending methodologies to incorporate multimodal data and improving agents' abilities to interpret complex structures, addressing challenges related to varying scales in design features [38]. Reliable incentive mechanisms for data sharing across devices and the application of advanced AI tools are crucial for enhancing AI-driven design methodologies [93].

Optimizing computational performance through parallelization and GPU computing, while integrating these frameworks with machine learning models for advanced design parameterization, will be pivotal for maintaining computational efficiency [94]. Future research should also explore optimizing edge computing resources for AIGC, federated learning techniques, and the implications of AIGC in emerging technologies such as the Metaverse [33].

In structural design, applying generative methodologies to additional structural elements and considering various load combinations, along with necessary construction processes for optimized designs, will be critical [82]. Future research could focus on improving computational efficiency, integrating machine learning methods for enhanced design proposals, and increasing models' sensitivity to aesthetic considerations and sustainability metrics [95].

Moreover, experimental validations of architectures on diverse robotic platforms and exploring long/short-term memory integration for improved learning and adaptation are essential areas for future exploration [6]. Enhancing the flexibility of platforms like AI2Apps and exploring integrations with LLMOps platforms could further improve capabilities in AI-driven design [7].

Additionally, optimizing methods to balance fidelity and speed, enhancing controllability, and addressing the Janus problem in perception are crucial for advancing text-to-3D technologies [46]. Refining parameterization processes, exploring higher resolution modeling, and integrating methodologies with CAD systems to facilitate automated design workflows are also important research directions [40].

The future of AI-driven design is abundant with opportunities for innovation, focusing on interactivity, robustness, interdisciplinary collaboration, and ethical considerations. These initiatives are poised to catalyze significant advancements in artificial intelligence, enhancing its capabilities and applications in design. By leveraging AIGC and integrating it into processes like evidence synthesis and creative writing, these efforts will streamline workflows and foster innovative design approaches. Furthermore, incorporating generative AI within augmented reality environments and participatory design fiction workshops highlights AI's potential to inspire creativity, leading to more inclusive and effective design solutions across diverse domains [58, 1, 52, 20, 2].

10 Conclusion

AI technologies have revolutionized product design by introducing novel pathways for enhancing creativity, efficiency, and functionality across diverse fields. The SLDA framework demonstrates AI's capacity to autonomously learn and apply design strategies to various challenges, achieving remarkable performance without depending on prior expert data. Generative design techniques have proven effective in reducing costs, weight, and development time, highlighting their transformative potential in product development. The application of deep learning models to manage complex geometries points to promising avenues for future research in uncertainty management and model interpretability.

The utilization of generative pre-trained transformers for bio-inspired design concepts illustrates AI's capability to drive innovative solutions. Nevertheless, the inherent power-seeking tendencies of AI systems necessitate robust governance and alignment strategies to mitigate risks. Incorporating ethical considerations into AI system design is imperative, as emphasized by the Ethics by Design approach, ensuring responsible and transparent deployment.

Research into co-creating AI experiences underscores the importance of viewing AI as a design material, fostering enhanced collaboration between designers and engineers to develop AI experiences that align with user needs. Addressing the ethical implications, accountability, and transparency of AI systems is crucial, requiring continuous engagement among stakeholders to navigate ethical challenges.

As AI technologies evolve, their influence on product design is set to grow, presenting new opportunities for innovation while addressing ethical and resource-related challenges. The future trajectory of AI-driven product design will likely involve increased interdisciplinary collaboration, facilitating advancements that harness AI's potential to create solutions that are more efficient, sustainable, and user-centric.

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