Interdisciplinary Approaches to Large Language Models in Industrial Design: A Survey

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Abstract

The integration of Large Language Models (LLMs) with design methodologies, such as industrial design, user requirement analysis, natural language processing, human-centered design, and design thinking, represents a significant advancement in creating innovative, user-centric solutions. This survey explores the transformative role of LLMs across these domains, highlighting their potential to enhance design processes, improve product functionality, and foster interdisciplinary collaboration. LLMs facilitate the modeling of complex design processes, enabling the development of solutions that are both functional and aesthetically pleasing, while addressing intricate user needs. The integration with Design Thinking methodologies, particularly in the context of the 4th industrial revolution, underscores the adaptability and creative enhancement potential of LLMs. Furthermore, LLMs contribute to educational methodologies by aligning cognitive tasks with human performance metrics, thus fostering innovative learning environments. Despite these advancements, challenges persist in computational requirements, ethical considerations, and interpretability, necessitating ongoing research to ensure responsible AI implementation. The survey concludes by emphasizing the importance of interdisciplinary approaches in advancing LLM applications, suggesting future research directions that include expanding language diversity in training data and improving model interpretability and ethical frameworks. As LLM technology continues to evolve, its integration with diverse design methodologies is anticipated to drive further innovation and efficiency, offering new opportunities for industry and academia.

1 Introduction

1.1 Significance of Integration

The integration of Large Language Models (LLMs) with diverse design methodologies marks a significant advancement in fostering innovation across multiple sectors. This integration is particularly prominent in industrial design, where the adoption of digital technologies can substantially enhance societal well-being [1]. LLMs facilitate the modeling of intricate design processes, enabling the development of solutions that are both functional and aesthetically appealing, thereby addressing the complex user needs characteristic of contemporary industrialized societies.

Design Thinking, which emphasizes creativity and user-centric problem-solving, greatly benefits from LLM integration. This methodology is vital in the context of the Fourth Industrial Revolution, where innovative solutions are essential [2]. The application of Design Thinking in hackathons, even among participants without formal training, illustrates the methodology's adaptability and the potential for LLMs to enhance creative processes [3]. Moreover, recent studies highlight the importance of co-creating AI experiences, underscoring the need to integrate AI with user experience design to drive innovation [4].

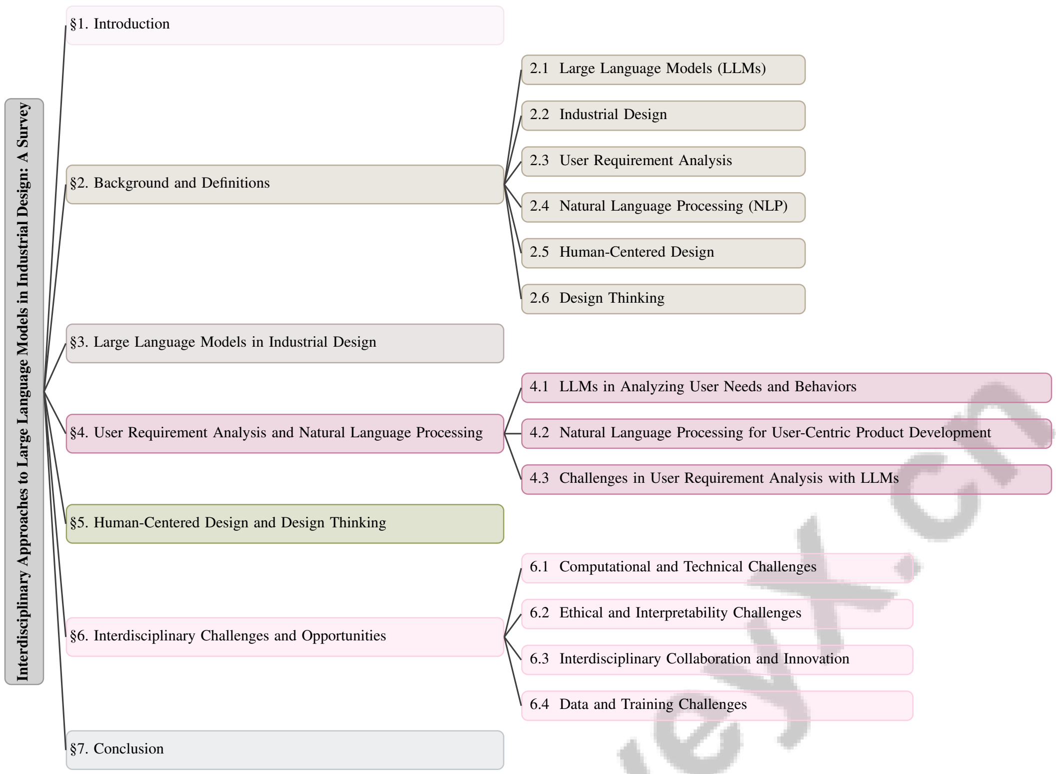

Figure 1: chapter structure

LLMs also play a crucial role in educational methodologies by facilitating the assessment of cognitive tasks, thereby aligning educational practices with human performance metrics [5]. This capability is essential for developing effective and engaging educational tools, fostering a more innovative learning environment.

In the realm of human-centered design, which prioritizes optimizing human-machine interactions, LLMs can significantly influence outcomes. Their integration with human-centered design methodologies emphasizes the importance of trust and a balanced perspective that merges technology with business insights [6]. This approach aligns with Learning Analytics principles, where a human-centered focus enhances teacher engagement and effectiveness [7].

1.2 Structure of the Survey

This survey is organized into several key sections that collectively investigate the interdisciplinary integration of Large Language Models (LLMs) within industrial design and related methodologies. The introduction establishes the significance of integrating LLMs with design methodologies, emphasizing their role in fostering innovation across various domains. Following this, Section 2 provides essential background and definitions, offering a comprehensive overview of core concepts such as LLMs, industrial design, user requirement analysis, natural language processing, human-centered design, and design thinking.

Section 3 explores LLM applications in industrial design, focusing on enhancing design processes, improving product functionality, and presenting case studies that showcase successful integrations. This section highlights LLMs' potential to streamline workflows and create aesthetically pleasing, functional products. In Section 4, the survey examines LLMs in user requirement analysis and natural language processing, emphasizing the analysis of user needs and behaviors for developing user-centric products while addressing challenges encountered in user requirement analysis with LLMs.

Section 5 discusses human-centered design and design thinking in the context of LLMs, underscoring the importance of empathetic and iterative problem-solving approaches. The principles of human-centered design are explored, including methodologies for integrating LLMs to enhance user-centric design. The Doble Diamante method is referenced as a structured approach guiding the creative process through discovery, definition, design, and development [2].

Section 6 identifies interdisciplinary challenges and opportunities, exploring computational, technical, ethical, and interpretability challenges, as well as the benefits of interdisciplinary collaboration in advancing LLM applications. Topics such as data privacy, ethical considerations, diverse abilities and needs, and the social context of technology use by children are crucial for responsible AI implementation [8].

The paper concludes with Section 7, providing a comprehensive summary of key findings, emphasizing the importance of interdisciplinary approaches in research, and identifying areas for future exploration. It discusses the broader implications of these findings for industry practices and academic scholarship, highlighting the potential role of artificial intelligence, particularly large language models like ChatGPT, in enhancing literature review processes and supporting students in their research endeavors [9, 10, 11, 12].The following sections are organized as shown in Figure 1.

2 Background and Definitions

2.1 Large Language Models (LLMs)

Large Language Models (LLMs) represent a significant breakthrough in AI, excelling in generating human-like text and performing complex reasoning tasks [13]. Transitioning from statistical methods to advanced neural networks, LLMs efficiently process vast textual data, crucial in domains like industrial design, where they enhance user interaction and foster innovative design concepts [4]. Their ability to autonomously navigate web pages and execute tasks simulates real-world interactions, aiding user requirement analysis [14]. LLMs also generate code for 3D modeling, essential for creating functional, aesthetically pleasing products [15].

Despite their capabilities, LLMs face challenges in higher-order reasoning. Approaches like Reinforcement Learning from Human Feedback (RLHF) and Self-Developing models are explored to improve alignment with human reasoning, enabling LLMs to autonomously generate improvement algorithms [13]. Integrating LLMs with qualitative research methodologies enhances understanding of user needs, aligning design with consumer requirements and addressing design complexities [16]. As LLMs evolve, their impact on industrial design and other fields will expand, driven by advancements and human expertise [13].

2.2 Industrial Design

Industrial design is a multidisciplinary field focused on creating functional, aesthetically appealing products, emphasizing user experience and market acceptance [17]. It plays a key role in integrating LLMs, aligning digital innovations with consumer needs and societal trends [1]. Design Thinking methodologies promote creativity and rapid prototyping, enabling designers to iterate product concepts informed by LLM insights [2]. LLMs enhance human-machine interaction simulation, aiding in the creation of intuitive, user-friendly products, consistent with human factors engineering [18]. They also empower designers to explore new design spaces, crucial for adapting to technological advancements and diverse consumer needs [19]. Frameworks like the AAA framework systematically embed design thinking into processes, fostering sustained innovation [20].

2.3 User Requirement Analysis

User requirement analysis is crucial in product design, focusing on understanding user needs and preferences by systematically gathering and interpreting user data [17]. Traditional methods face challenges with large text corpora, where LLMs transform the process by inferring underlying user goals and psychological needs, offering deeper insights [21]. This capability is vital for capturing complex user needs, which traditional systems struggle with due to limited reasoning abilities [22]. LLMs facilitate collaboration among design agents, addressing inter-agent communication complexities in innovative design contexts [23]. This collaborative approach is essential for managing vast design alternatives, particularly for 'wicked' problems [19]. By leveraging LLMs, designers can synthesize information and generate scholarly commentary, overcoming challenges in literature reviews [9]. Adapting general-purpose retrieval-augmented generation (RAG) systems for user

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requirement analysis enhances precision and relevance by incorporating domain-specific knowledge [24]. LLM integration significantly enhances the efficiency and accuracy of user requirement analysis, improving user-centric product design through advanced prompting strategies [9, 25, 26, 27, 12].

2.4 Natural Language Processing (NLP)

Natural Language Processing (NLP) is a critical AI domain focusing on machine-human interaction through natural language, enhancing user-centric design processes [28]. LLMs have transformed NLP, providing exceptional language understanding and generation capabilities essential for user-centric product development. Integrating NLP with LLMs enhances design by offering robust frameworks for evaluating LLM outputs, enriching the design process with nuanced insights [29]. Advancements in neural networks have revolutionized NLP, improving model performance across various tasks [30]. NLP also plays a vital role in developing Explainable AI (XAI), addressing model interpretability [31]. This ensures equitable, accurate outputs, crucial for user-centric designs. Integrating NLP with LLMs supports design thinking, deepening understanding of digital penetration steps [1].

2.5 Human-Centered Design

Human-Centered Design (HCD) prioritizes user needs, ensuring solutions align with human values and requirements [32]. Characterized by empathy, iterative problem-solving, and a holistic perspective, HCD considers the broader context of design solutions [33]. LLMs enhance HCD by automating tasks and interpreting user queries, fostering intuitive interfaces [26]. They enhance user control and trust in systems like AutoML [6]. Challenges in expressing empathy through AI highlight the need for affective computing and resonance theory integration [34]. HCD's iterative nature is supported by methodologies like Human-in-the-Learning-Loop (HILL) Design Cycles, blending design thinking and agile processes with machine learning [35]. Design Thinking employs iterative, collaborative strategies to tackle complex problems [36]. In education, HCD principles create authentic design experiences, preparing future designers [7]. The Autonomous Rollator case study exemplifies aligning solutions with end-user needs [37]. LLM integration within HCD frameworks emphasizes maintaining a user-centric focus in AI development, enhancing satisfaction and engagement [30].

2.6 Design Thinking

Design Thinking is a user-centric methodology emphasizing creativity and iterative problem-solving through structured interventions [38]. It involves understanding, defining, ideating, and prototyping phases, fostering solutions aligned with user needs. Cultivating a Design Thinking mindset is crucial, though measurement challenges persist [39]. Integrating LLMs within Design Thinking transforms generative AI from passive tools to active ideation participants [40]. The CHAI-DT framework exemplifies this shift, enhancing creative output and supporting user-centered, technologically advanced solutions. In hackathon settings, Design Thinking aids participants in navigating limited formal design training through effective iteration on software prototypes [3]. Its integration within LLM frameworks presents transformative opportunities for enhancing creativity and innovation across fields like education and management. Research indicates Design Thinking as an active learning strategy significantly influences students' innovative thinking and higher-order cognitive skills, equipping them to navigate complex challenges [39, 41, 42]. As LLMs evolve, their integration with Design Thinking methodologies will expand, providing enhanced tools for addressing complex design challenges and developing user-resonant solutions.

In recent years, the integration of Large Language Models (LLMs) into industrial design has emerged as a pivotal development, warranting a comprehensive examination of its implications. This integration not only enhances design processes but also significantly improves product functionality. Figure 2 illustrates the hierarchical structure of this integration, highlighting key areas such as methodologies and applications. Each primary category is meticulously divided, showcasing case studies that demonstrate the transformative role of LLMs in optimizing workflows, enhancing creativity, and improving functionality across various domains. By examining these dimensions, we can better understand the multifaceted benefits that LLMs bring to the field of industrial design.

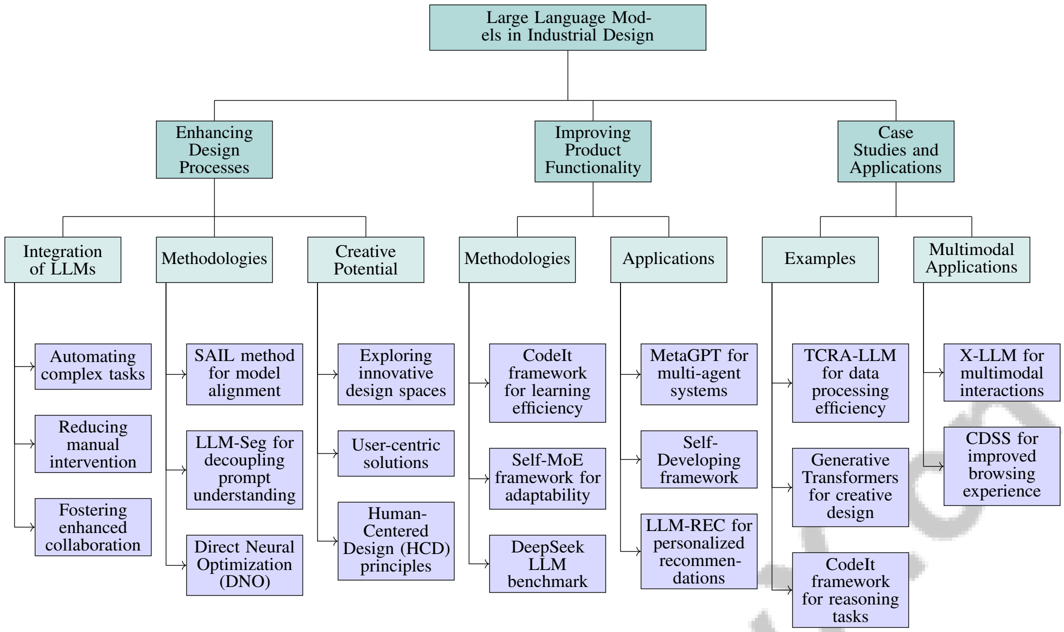


Figure 2: This figure illustrates the hierarchical structure of integrating Large Language Models (LLMs) into industrial design, highlighting key areas such as enhancing design processes, improving product functionality, and showcasing case studies and applications. Each primary category is further divided into methodologies and applications, demonstrating the transformative role of LLMs in optimizing workflows, enhancing creativity, and improving functionality across various domains.

3 Large Language Models in Industrial Design

3.1 Enhancing Design Processes

The integration of Large Language Models (LLMs) into industrial design workflows significantly optimizes design processes by automating complex tasks and reducing manual intervention, thereby fostering enhanced collaboration within design teams. The Self-Improving Efficient Online Alignment of Large Language Models (SAIL) method exemplifies this, refining model alignment through iterative sample generation and preference label regulation, streamlining design workflows [43]. Additionally, the LLM-Seg method enhances design workflows by decoupling prompt understanding from the segmentation process, offering greater flexibility and performance in design tasks [44]. This separation is crucial for adapting to the dynamic requirements of industrial design, where distinct approaches are often necessary.

Direct Neural Optimization (DNO) further refines LLMs by optimizing preference feedback through a regression-based learning strategy, aligning model outputs with user feedback to meet user expectations and design goals [45]. These methodologies not only boost design efficiency but also expand the creative potential of design teams. By leveraging LLM capabilities, designers can explore innovative design spaces and methodologies, fostering user-centric solutions and improving user experiences through Human-Centered Design (HCD) principles tailored for LLMs. Research indicates that applying HCD principles effectively addresses diverse user needs, leading to enhanced interactions and outcomes in software learning environments [46, 26]. This evolution in design workflows underscores the transformative role of LLMs in industrial design, paving the way for sophisticated methodologies across various domains.

3.2 Improving Product Functionality

LLMs are increasingly enhancing product functionality through improved learning efficiency and adaptability. The CodeIt framework exemplifies this by employing an iterative approach that combines program sampling, hindsight relabeling, and prioritized experience replay, collectively boosting LLM learning efficiency [47]. This methodology is crucial for refining product functionality by enabling models to learn from diverse experiences and evolve over time.

The Self-MoE framework significantly enhances base LLM performance, achieving improved accuracy and adaptability without extensive human supervision or additional parameters [48]. This capability is vital for developing products that are functional and responsive to changing user needs and environmental conditions. The DeepSeek LLM benchmark further illustrates LLM contributions to product functionality, demonstrating superior performance in mathematics and coding tasks compared to models like LLaMA-2 [49]. This benchmark highlights LLMs' potential to enhance computational capabilities, thereby improving overall functionality and user experience.

MetaGPT utilizes Standard Operating Procedures (SOPs) to enhance multi-agent system capabilities, achieving state-of-the-art performance in code generation tasks [50]. This integration facilitates the development of products that efficiently execute complex tasks, ultimately improving functionality. The Self-Developing framework also enhances product functionality by allowing LLMs to autonomously discover effective model-improvement algorithms that consistently outperform both the seed model and human-designed methods [13]. This autonomous capability ensures products can evolve and adapt to new challenges, maintaining relevance and effectiveness over time.

The integration of LLMs into product development processes significantly enhances functionality through advanced learning, adaptability, and computational capabilities. These advancements illustrate the transformative potential of LLMs in creating innovative products that not only enhance their functionality but also adapt to evolving user preferences and technological landscapes. Techniques like LLM-REC improve personalized recommendations by leveraging diverse prompting strategies, while frameworks like START enhance the credibility of information generated by LLMs through improved attribution capabilities. These developments demonstrate how LLMs can effectively meet the complex demands of various applications, from recommendation systems to academic research support, thereby redefining user interactions across multiple domains [9, 27, 51, 52, 12].

3.3 Case Studies and Applications

The integration of LLMs into industrial design is evidenced by case studies and applications showcasing their transformative potential. The TCRA-LLM, evaluated using the Food-Recommendation DB (FRDB) dataset, demonstrated a 65% reduction in token size while achieving a 0.3% accuracy improvement, highlighting its efficiency in processing complex data [53]. In creative design, Generative Transformers have successfully generated novel and useful design concepts, illustrating LLMs' potential to enhance creativity and innovation in the design process [54].

The CodeIt framework further exemplifies LLM application in industrial design, achieving state-of-the-art performance on the Abstraction and Reasoning Corpus (ARC) by solving 59 out of 400 evaluation tasks [47]. This accomplishment underscores LLMs' ability to tackle complex reasoning tasks, essential for developing sophisticated design solutions. The multimodal application of LLMs is demonstrated by X-LLM, which exhibits impressive multimodal chat abilities, achieving a relative score of 84.5% compared to GPT-4 on a synthetic multimodal instruction-following dataset, indicating its potential applications in industrial design where multimodal interactions are increasingly vital [55].

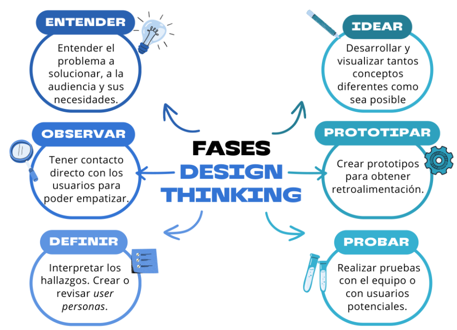
A case study focusing on kitchen accessory containers from the Alessi collection highlights the use of Context-Dependent Semantic Search (CDSS) to significantly improve the browsing experience for designers [17]. This application enhances user experience and facilitates design exploration, reflecting LLMs' broader impact on industrial design processes.

These case studies collectively illustrate the diverse integration of LLMs into industrial design, enhancing functionality, creativity, and user interaction. As LLM technology advances, its integration into industrial design is expected to expand significantly, facilitating innovative solutions and enhancing efficiency throughout the product development process. This evolution is driven by LLMs' ability to synthesize domain knowledge, generate creative concepts, and improve personalized recommendations, ultimately transforming how designers and engineers approach their work [9, 27, 54, 12].

As shown in Figure 3, large language models are increasingly leveraged in industrial design to enhance creativity and streamline the development of innovative products and services. The figure showcases

Type of Involvement	#
The **UX design team collaborated with engineers**, product managers or others, and jointly developed an idea for a new product or service that utilizes machine learning	12
The **UX design team gave an interactive form** to a machine learning idea that came from others (e.g. software developers or engineers)	8
The **UX design team generated a novel design concept** utilizing machine learning, which was presented and then selected for integration into a new product or service	7

(a) The UX design team collaborated with engineers, product managers, and others to jointly develop an idea for a new product or service that utilizes machine learning.[46]



(b) Design Thinking Phases[56]

Figure 3: Examples of Case Studies and Applications

two pivotal examples highlighting these models' integration in the design process. The first example depicts a collaborative effort where a UX design team worked alongside engineers and product managers to conceptualize a new machine learning-driven product, emphasizing the interdisciplinary nature of modern design projects. The second example illustrates the Design Thinking methodology, guiding teams through phases of understanding, observing, defining, and testing. Each phase is visually represented with intuitive icons and Spanish labels, underscoring the global applicability of this process. Together, these examples reflect the transformative potential of large language models in fostering innovation and improving industrial design practices [46, 56].

4 User Requirement Analysis and Natural Language Processing

Incorporating advanced technologies, especially Large Language Models (LLMs), has become crucial for user requirement analysis, enhancing our comprehension of user needs and behaviors. This section explores the transformative influence of LLMs on analyzing user interactions and preferences, ultimately supporting more informed design decisions. The following subsection highlights specific applications of LLMs in understanding user needs, emphasizing their impact on design processes and outcomes.

4.1 LLMs in Analyzing User Needs and Behaviors

LLMs have revolutionized the analysis of user needs and behaviors, offering critical insights that inform design decisions across various fields. Their capability to process extensive datasets provides a nuanced understanding of user preferences, essential for crafting user-centric designs. Unlike traditional recommendation systems, which often miss complex, latent relationships, LLMs leverage advanced reasoning, such as the LLM-Seg method, to enhance segmentation tasks by analyzing intricate prompts [44].

In collaborative design, co-creation allows designers to express their needs and expectations for AI behavior, guiding design decisions effectively [4]. This is especially beneficial in interactive settings, where evaluating agent capabilities through benchmarks is key to understanding LLMs' interpretation of user data.

LLMs excel in generating diverse concepts, inspiring designers beyond conventional methods, particularly in creative domains where vast knowledge bases can lead to innovative solutions. By synthesizing multimodal user data, they offer a comprehensive framework for analyzing user inputs, leveraging commonsense reasoning and contextual understanding to enhance text-based recommendations, aligning closely with user preferences and refining design evaluation criteria [27, 25, 12].

In healthcare, LLMs analyze diverse patient data from Electronic Health Records (EHRs), supporting informed decisions in clinical workflows, diagnostics, and treatment plans, thus improving patient care and operational efficiency [57, 27, 11, 12, 58]. These capabilities highlight LLMs' potential to enhance user-centric design by providing deep insights into user behaviors and preferences.

Furthermore, LLMs enhance interactions between humans and intelligent systems, addressing AI advancement challenges. Through self-developing frameworks that autonomously generate improved models without superior teacher models or human direction, LLMs contribute to more precise and relevant design decisions [13].

The deployment of LLMs in user needs analysis marks a significant advancement in design decision-making. Their sophisticated analytical capabilities offer profound insights into user preferences, fostering the development of responsive, user-centric design solutions mindful of broader systemic considerations, including impacts on non-users, future generations, and environmental sustainability. This approach aligns with human-centered design principles and addresses critiques of traditional user-centric frameworks, ensuring a comprehensive understanding of design implications across contexts [59, 11]. As LLM technology evolves, its role in shaping design decisions and enhancing user experience is expected to broaden, opening new avenues for innovation across diverse fields.

4.2 Natural Language Processing for User-Centric Product Development

Natural Language Processing (NLP) is pivotal in developing user-centric products by enabling sophisticated analysis of extensive textual datasets. This capability is crucial for understanding consumer behavior and market dynamics, facilitating the creation of products that effectively address user needs [28]. Integrating NLP into product development emphasizes augmenting human capabilities, fostering a collaborative environment where technology enhances human decision-making rather than replacing it [31].

Recent advancements in neural embeddings and architectures have significantly enhanced NLP model performance, allowing for more nuanced insights into user preferences and behaviors, essential for developing resonant products [30]. Pretrained models from platforms like Hugging Face provide robust frameworks for deploying state-of-the-art NLP solutions, enriching the product development process with detailed user insights.

A critical aspect of NLP in user-centric product development is its ability to create tailored reasoning frameworks that enhance interpretive analysis, facilitate scalable fact-checking, and improve requirements engineering through user feedback and stakeholder input. This personalized approach integrates human-centered design principles, ensuring that NLP technologies effectively address users' nuanced needs while promoting collaboration between machines and human experts [60, 61, 11]. By linking user profiles and behavioral sequences through causal and logical inferences, NLP enhances the interpretability of user interests and informs product design decisions. Additionally, incorporating feedback mechanisms allows NLP models to dynamically interact with their environment, adapting their logic based on user interactions and evolving preferences.

Despite significant advancements, challenges persist in achieving explainability, particularly in deep learning models. Addressing these challenges is vital for fostering trust and transparency in user-centric product development [31]. As NLP technologies continue to evolve, their integration into product development is expected to expand, offering new opportunities for innovation and efficiency in meeting consumer demands.

4.3 Challenges in User Requirement Analysis with LLMs

The application of LLMs in user requirement analysis presents several challenges that complicate their effective use in capturing and interpreting user needs. A significant challenge is the inherent ambiguity and variability in language across different domains and cultures, necessitating a deep contextual understanding that LLMs may struggle to achieve [28]. This complexity is exacerbated by the need for models to adapt to the unique terminologies and intricacies of specific fields, such as finance, where existing benchmarks often fall short [62].

Another critical issue is the generation of hallucinations by LLMs, resulting in outputs that are factually incorrect or logically inconsistent, undermining the reliability of user requirement analysis [63]. This problem is intensified by distribution shifts in reward learning stemming from statistical dependencies on responses and preferences, a challenge inadequately addressed by current methods [43].

Moreover, traditional methodologies often fail to effectively handle unstructured data, as seen in big data projects, highlighting inefficiencies that can arise when the evaluation phase is delayed [64]. This is particularly pertinent for LLMs, where evaluation timing and methodology are crucial for accurate requirement analysis.

The reliance on sentiment analysis as a proxy for bias detection in methods like LLMBI presents limitations, potentially overlooking subtleties beyond emotional tone, thereby affecting the depth of user requirement analysis [65]. Additionally, the lack of long-term adoption of proposed tools and insufficient industrial validation in NLP for Requirements Engineering (NLP4RE) research complicates the integration of LLMs into user requirement analysis [60].

Existing benchmarks also struggle to capture the subjective and diverse nature of LLM outputs, leading to unreliable evaluations that hinder effective user requirement analysis [25]. Furthermore, determining whether iterative post-training methods genuinely enhance LLM capabilities or result in regressions remains a critical concern [66].

In complex network environments, monitoring performance and diagnosing faults pose additional challenges for LLMs in conducting user requirement analysis effectively [67]. Collectively, these challenges highlight the need for ongoing research and development to improve the effectiveness and applicability of LLMs in user requirement analysis, ensuring they can meet the diverse and evolving needs of users.

5 Human-Centered Design and Design Thinking

5.1 Principles of Human-Centered Design

Human-Centered Design (HCD) emphasizes aligning design solutions with user needs and values, ensuring usability and satisfaction [37]. Integrating Large Language Models (LLMs) into this process enhances the development of user-centric solutions. Empathy is central to HCD, fostering a deep understanding of users' experiences and aligning AI capabilities with user-centered needs, promoting iterative problem-solving [4]. The Double Diamond method exemplifies this approach, emphasizing research, definition, design, and prototyping to create innovative, user-focused designs [2].

User engagement is vital in HCD, particularly in participatory design approaches that respect human dignity, privacy, and autonomy, especially in AGI development [68]. Informal design practices, such as hackathons, highlight user-centered problem exploration and iterative prototyping, fostering innovative solutions [3]. Iterative problem-solving in HCD involves continuous feedback, leading to refined solutions that align with user needs. This approach supports responsible AI implementation, maintaining trust and aligning with human-centered design principles [6].

5.2 Integration of LLMs in Human-Centered Design

Integrating LLMs into Human-Centered Design (HCD) methodologies transforms user engagement, fostering collaboration between users and technologists. This integration aligns with participatory design and agile development principles, emphasizing user involvement throughout the design process [68]. Leveraging LLMs enhances human creativity, aiding in the development of user-centric solutions. The Double Diamond method provides a structured framework for this integration [2].

Methodologies for integrating LLMs into HCD focus on creating intuitive interactions through natural language processing, broadening technology accessibility and ensuring inclusivity [9, 26, 59, 56, 12]. Incorporating LLMs into design education enhances learners' engagement in design processes, deepening their understanding of user needs. A significant challenge is overcoming technical perfectionism, which can limit user engagement. Addressing this requires methodologies emphasizing HCD principles, such as integrating causal pathway diagrams (CPDs) into the design process. CPDs enhance early design stages by supporting divergent and convergent thinking, facilitating stakeholder communication, and reducing cognitive workload for designers [69, 70, 71, 72, 35].

Incorporating LLMs into design thinking workshops for software engineering environments enhances the ability to address complex stakeholder needs and facilitates effective problem identification and software development transitions [38, 35, 33, 72, 12]. Techniques such as warm-up exercises, knowledge sharing, and feedback mechanisms further facilitate the integration of design thinking within agile workflows.

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5.3 User-Centric Design and Human Factors

User-centric design, grounded in human factors, ensures solutions are functional and resonate intuitively with users. This approach prioritizes user involvement throughout the design process, enhancing satisfaction and engagement [73]. Integrating LLMs into this framework enhances understanding of user needs, leveraging advanced computational capabilities to interpret complex data and generate insights for informed design decisions.

LLMs enable depth and scale in understanding user needs, involving diverse stakeholders [74]. This capability is crucial for ensuring solutions are inclusive and reflect varied user perspectives. However, challenges in large-scale participatory design may lead to oversimplification and overlook nuanced user needs [75]. HCD methodologies emphasize empathy and understanding user needs, essential for effective engineering solutions [70]. Integrating LLMs can enhance the design process by providing AI-assisted tools that support designers in navigating complex problem spaces, while avoiding oversimplification or reliance solely on AI-generated suggestions without thorough research [69].

6 Interdisciplinary Challenges and Opportunities

The integration of Large Language Models (LLMs) into design processes presents diverse challenges including computational, technical, ethical, and collaborative aspects. Addressing these is key to ensuring LLMs effectively meet user needs across varied contexts.

6.1 Computational and Technical Challenges

Integrating LLMs into design workflows introduces computational and technical hurdles such as data quality assurance, hallucination management, and effective attribution methods, which can impede their application in creative and technical fields [51, 52, 12]. The extensive computational resources required for training and deploying these models necessitate more efficient architectures to enhance performance and accessibility. High memory and computational demands, particularly when models exceed available DRAM, complicate integration [76], and the costs of using large models as verifiers further hinder efficiency [77]. Existing benchmarks often inadequately represent long-horizon tasks and lack metrics capturing agent performance nuances in dynamic environments.

A significant obstacle is the reliance on scalar reward functions, which inadequately reflect human preferences, limiting model alignment with user expectations [45]. Additionally, dependency on specific datasets for benchmarks restricts applicability across diverse problem types, while the iterative training's computational demands could hinder broader adoption [66]. The SAIL method exemplifies these challenges, requiring a unified optimization framework for online Reinforcement Learning from Human Feedback (RLHF) to align LLMs with human preferences [43], while the Reasoning Advantage reward function struggles to distinguish meaningful reasoning from random sequences [78].

Some approaches autonomously generate high-performance algorithms, surpassing human-designed methods [13], yet managing expectations and trust in AI remains challenging, closely linked to technical hurdles [6]. Ongoing research is essential to improve LLM integration, enhancing adaptability and effectiveness to meet evolving user requirements, including literature reviews and personalized recommendations. Innovative prompting strategies and input augmentation techniques hold potential to unlock LLMs' full capabilities, leading to improved outcomes in academic and practical settings [9, 27].

6.2 Ethical and Interpretability Challenges

Deploying LLMs necessitates addressing ethical and interpretability challenges, emphasizing transparency and alignment with human values. A significant ethical concern is reliance on offline datasets for LLM alignment, potentially leading to biased outcomes and inadequate coverage of response-query pairs [43]. Ethical frameworks are needed to guide responsible AI use in alignment with societal values.

Transparency in LLM applications is crucial, particularly in complex environments where clear interpretation of user inputs and AI outputs is necessary. This extends to LLMs' self-improvement mechanisms, which must align with ethical standards without compromising user trust. The ability of LLMs to explain their predictions raises questions about explanation faithfulness and interpretability, critical for maintaining user confidence. Current studies often lack formal definitions of explainability and standardized evaluation processes, complicating assessment [31].

Ethical considerations in Artificial General Intelligence (AGI) development highlight the necessity of prioritizing human values, ensuring AI technologies respect and enhance human dignity. This includes integrating ethical considerations throughout project phases and emphasizing continuous evaluation and transparency. A nuanced evaluation framework is essential to discern genuine progress from regressions in self-improvement practices, necessitating comprehensive metrics [66].

6.3 Interdisciplinary Collaboration and Innovation

Interdisciplinary collaboration is vital for advancing LLM applications, fostering innovative solutions across domains. Integrating Design Thinking into traditional methodologies enhances user satisfaction and aligns products with user needs, underscoring the importance of insights from various academic disciplines. This enables LLMs to autonomously improve performance and adapt to new tasks with minimal human oversight, streamlining processes like literature reviews and academic writing [9, 27, 12].

Collaboration between designers and AI engineers bridges gaps in AI experience design, facilitating co-creation of AI materials and applications. Utilizing design probes incorporating user data allows teams to define desirable AI characteristics, enhance divergent thinking, and validate design concepts, improving AI system effectiveness and fostering deeper understanding of AI capabilities and limitations [9, 4]. The Double Diamond method illustrates the benefits of interdisciplinary collaboration in generating innovative solutions by leveraging diverse perspectives for comprehensive design outcomes.

In Natural Language Processing (NLP), collaboration among experts in AI, linguistics, and computer science is crucial for developing sophisticated models addressing complex language tasks, enabling meaningful human-computer interactions [10, 12, 28]. The LLM-Seg method benefits from interdisciplinary insights, handling complex prompts and performing competitively against existing models.

Integrating neural network models with interdisciplinary insights enhances model interpretability, fostering user trust and understanding. Future research should focus on developing models that efficiently learn from limited data, incorporating multi-modal approaches, and enhancing neural network interpretability. Active stakeholder participation in design processes is vital for effective LLM application implementation, encouraging integration of diverse perspectives and expertise to address complexities in academic contexts [9, 25, 11, 27, 12]. This collaborative approach ensures AI technologies respect and enhance human dignity, integrating ethical considerations throughout project phases.

6.4 Data and Training Challenges

Integrating LLMs into design processes presents significant challenges related to data availability and training complexities. Effective training requires sophisticated data management strategies given the inherent complexity of machine learning models [79]. Designing user interfaces for explanation purposes necessitates interdisciplinary collaboration to enhance model transparency and address diverse user needs [79].

A major challenge in training LLMs is integrating human factors into model design, as these models often struggle with complex, contextual claims necessary for nuanced understanding [61]. This difficulty is pronounced when models interpret diverse and dynamic user inputs, highlighting the need for robust datasets capturing real-world interaction complexities.

Potential data contamination and noise from self-generated synthetic data, as seen in methods like Self-MoE, underscore the importance of rigorous monitoring to maintain data quality and integrity [48]. This challenge is compounded by ethical considerations and security vulnerabilities associated with self-improving agents, necessitating comprehensive strategies for responsible and secure LLM training [80].

Future research should focus on theoretical justifications of self-correction, developing comprehensive evaluation frameworks, and integrating model editing techniques to enhance self-correction processes [81]. Advancing autonomous self-evolution frameworks and exploring diverse and hierarchical evolution objectives are crucial for strengthening self-evolving mechanisms' theoretical foundations [82].

Challenges in achieving consensus on human-centered values further complicate data and training processes, as these values are integral to effective LLM integration [68]. Clear communication and understanding between designers and AI engineers are critical for effective co-creation, emphasizing the need for improved collaboration frameworks [4].

Refining the training pair construction process and exploring additional data sources are essential for enhancing Direct Neural Optimization (DNO) scalability [45]. Establishing standardized metrics for evaluating explanations and exploring trade-offs between explainability and model performance are vital areas for future research, particularly in addressing fidelity in explanations [31].

7 Conclusion

This survey highlights the pivotal influence of Large Language Models (LLMs) in transforming design methodologies and fostering interdisciplinary innovation. By integrating LLMs into industrial design, the development of user-centric solutions that are both functional and aesthetically appealing is significantly enhanced, aligning with human-centered design principles. This integration not only broadens the scope of human factors engineering but also opens new avenues for research and application. The findings underscore the importance of context-dependent semantic similarity in assisting designers to identify pertinent resources, suggesting a need for further exploration of its integration with existing methodologies. The potential of tools like the Supermind Ideator in enhancing creative problem-solving across various fields is noted, pointing to promising directions for future research in merging LLMs with design methodologies. Additionally, benchmarks such as DeepSeek provide valuable insights into scaling laws and model performance, indicating areas for future research to enhance LLM capabilities. Ethical considerations remain crucial in AI implementation, emphasizing the alignment of AI technologies with human values to maintain societal trust. The necessity for inclusive design approaches, particularly in addressing specific user needs such as those of children, is highlighted. Furthermore, LLM-based strategies offer significant enhancements in network operations, providing valuable insights for network management. Future research should focus on cost-effective deployment alternatives and strategies for enabling offline capabilities to ensure broader applicability. Advancements in few-shot grounded planning and notable improvements in quantization with LLM-QAT call for further exploration and refinement, underscoring the need for continued research in these areas.

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