Journal of Information Systems Engineering and Management
2026, 11(3s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Human-Centered Design of Generative AI Systems for Personalized Media and Enterprise Products

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ARTICLE INFO

ABSTRACT

Generative artificial intelligence is increasingly embedded in personalized media platforms and enterprise products, yet many systems remain optimized for technical performance rather than human experience. This study examines how human-centered design principles can be systematically integrated into generative AI systems to enhance personalization, usability, trust, and ethical alignment. Using a mixed-methods research framework, the study evaluates generative AI prototypes across media and enterprise contexts by combining user interaction metrics, experiential assessments, and governance-oriented indicators. The results demonstrate that deeper personalization and context-aware generation significantly improve perceived usefulness, interpretability, and user trust while reducing cognitive workload. Visual and statistical analyses further reveal a synergistic interaction between personalization depth and contextual awareness, highlighting their combined influence on sustained engagement and acceptance. Ethical transparency and explainability emerge as critical enablers of adoption, reinforcing the importance of embedding governance mechanisms directly into system design. Overall, the findings establish a human-centered design framework that supports the development of generative AI systems that are not only intelligent but also trustworthy, adaptive, and aligned with diverse user needs in media and enterprise environments.

Keywords: Human-centered design; Generative AI; Personalization; User trust; Media systems; Enterprise products

Introduction

The growing influence of generative AI in media and enterprise ecosystems

Generative artificial intelligence has rapidly transitioned from an experimental capability to a foundational technology shaping modern media production and enterprise product development (Onyejelem & Aondover, 2024). Advances in large language models, generative visual systems, and multimodal architectures have enabled organizations to automate content creation, personalize user experiences, and accelerate decision-making at unprecedented scales (Chen et al., 2024). In media platforms, generative AI supports dynamic storytelling, adaptive advertising, and real-time audience engagement, while in enterprise contexts it underpins intelligent assistants, product recommendation engines, design automation tools, and knowledge management systems (Onyejelem & Aondover, 2024). Despite these technological gains, many generative AI systems remain primarily optimized for computational efficiency and output quality, often overlooking the nuanced needs, expectations, and values of end users who ultimately interact with these systems (Dua & Patel, 2024).

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The need for human-centered design in generative AI systems

Human-centered design emphasizes designing technologies around human goals, behaviors, limitations, and socio-cultural contexts rather than forcing users to adapt to complex systems (Adewusi et al., 2022). In the context of generative AI, this perspective is particularly critical because outputs are not merely functional responses but communicative artifacts that influence perception, trust, creativity, and decision-making. Poorly designed generative systems can lead to cognitive overload, misinterpretation of AI outputs, reduced user agency, and ethical concerns such as bias amplification or lack of transparency (Umakor, 2022). Integrating human-centered design principles ensures that generative AI systems remain interpretable, controllable, and aligned with user intent, enabling meaningful collaboration between humans and AI rather than passive consumption of algorithmic outputs (Peláez et al., 2024).

Personalization as a core requirement for next-generation AI products

Personalization has emerged as a defining characteristic of successful media platforms and enterprise products. Users increasingly expect systems to adapt to their preferences, workflows, cultural contexts, and evolving goals (Gorgoglione et al., 2019). Generative AI offers powerful mechanisms for personalization by learning from interaction histories, contextual signals, and feedback loops to tailor content, interfaces, and recommendations. However, personalization without a human-centered lens risks becoming intrusive, opaque, or misaligned with user values (Torkamaan et al., 2024). Designing personalized generative systems therefore requires balancing adaptability with user control, ensuring that individuals understand why certain outputs are generated and how personalization parameters can be adjusted (Jiang et al., 2022). This balance is essential for sustaining long-term engagement and trust in AI-driven products.

Challenges in aligning generative intelligence with human values

Despite its potential, generative AI introduces significant design challenges related to explainability, fairness, accountability, and emotional resonance (Pescapè, 2024). Users may struggle to assess the reliability of generated outputs, especially in enterprise decision-support systems where errors can have substantial consequences. In media applications, generative content can blur boundaries between human creativity and machine synthesis, raising questions of authenticity and authorship (Hughes et al., 2021). Human-centered design addresses these challenges by embedding ethical considerations, transparent interaction mechanisms, and feedback-driven refinement processes directly into system architecture (Fasouli et al., 2024). By foregrounding human values, designers can mitigate risks while enhancing the perceived usefulness and legitimacy of generative AI systems.

The role of interdisciplinary approaches in human-centered generative AI

Designing effective human-centered generative AI systems requires collaboration across disciplines, including human–computer interaction, cognitive psychology, design thinking, data science, and organizational studies (Demirel et al., 2024). Technical model performance must be evaluated alongside usability metrics, user satisfaction, and contextual relevance (Hussain et al., 2018). For enterprise products, this includes aligning AI behaviors with organizational workflows and decision hierarchies, while in media systems it involves understanding audience engagement patterns and creative practices. An interdisciplinary approach enables designers to translate abstract human needs into concrete system requirements, ensuring that generative AI augments human capabilities rather than replacing them (Onatayo et al., 2024).

Research objectives and contribution of the present study

This study aims to develop a structured framework for the human-centered design of generative AI systems tailored to personalized media and enterprise products. It seeks to identify key design dimensions, user interaction principles, and evaluation criteria that support effective personalization

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while maintaining transparency, usability, and ethical alignment. By synthesizing insights from design theory and generative AI system development, this research contributes a practical and conceptual foundation for building next-generation AI products that are not only intelligent but also humane, trustworthy, and responsive to diverse user contexts.

Methodology

The overall research design and methodological framework

This study adopts a mixed-methods research design to systematically examine the human-centered design of generative AI systems for personalized media and enterprise products. The methodology integrates system-level analysis, user-centric evaluation, and data-driven modeling to capture both technical performance and human experience dimensions. A sequential exploratory approach is employed, beginning with qualitative requirement elicitation, followed by quantitative experimentation and validation. This structure enables the alignment of human-centered design principles with measurable generative AI outcomes while maintaining contextual relevance across media and enterprise application domains.

The selection of application domains and system prototypes

Two primary application domains are considered: personalized media platforms and enterprise productivity products. For each domain, a generative AI prototype is developed using large language and multimodal generation capabilities. Media prototypes focus on adaptive content generation, narrative variation, and audience-specific tone modulation, whereas enterprise prototypes emphasize task assistance, document generation, and workflow-aware recommendations. Domain-specific constraints, such as content sensitivity in media and decision criticality in enterprise environments, are explicitly incorporated into system configuration. This comparative design enables cross-domain analysis of human-centered requirements and system behavior.

The identification of human-centered design variables and parameters

Human-centered variables are grouped into cognitive, behavioral, and experiential dimensions. Cognitive parameters include perceived usefulness, mental workload, interpretability, and trust in generated outputs. Behavioral parameters capture interaction frequency, revision cycles, personalization adjustments, and response acceptance rates. Experiential parameters assess satisfaction, emotional alignment, and perceived creative support. System-level parameters include personalization depth, context window size, feedback incorporation rate, latency, and output consistency. Ethical and governance-related variables, such as bias perception, transparency cues, and user control mechanisms, are also embedded as evaluative dimensions.

The personalization and generative model configuration

Personalization is operationalized through adaptive user profiles constructed from interaction history, contextual metadata, and explicit preference inputs. Generative model parameters include temperature, top-k and top-p sampling, prompt structuring, and reinforcement from user feedback. Contextual awareness is enhanced using retrieval-augmented generation to incorporate relevant enterprise documents or media style guides. A controlled parameter-tuning process ensures that variations in outputs can be directly linked to changes in personalization and human-centered design features, enabling systematic evaluation of their effects.

The data collection and user study protocol

Data are collected through structured user studies involving participants from media production and enterprise knowledge-work backgrounds. Participants interact with the generative AI prototypes over

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multiple sessions, allowing longitudinal observation of adaptation and learning effects. Quantitative data include task completion time, output acceptance scores, personalization usage metrics, and system performance logs. Qualitative data are obtained through semi-structured interviews, think-aloud protocols, and post-interaction surveys. This dual data stream ensures comprehensive capture of both observable behavior and subjective user experience.

The analytical techniques and evaluation metrics

Quantitative analysis employs descriptive statistics, multivariate analysis, and regression modeling to examine relationships between personalization parameters, system performance, and human-centered outcomes. Factor analysis is used to identify latent dimensions of user experience, while comparative statistical tests assess differences between media and enterprise contexts. Qualitative data are analyzed using thematic coding to extract recurring patterns related to trust, control, creativity, and usability. Model explainability and fairness are assessed using output consistency checks, bias audits, and user-perceived transparency scores, integrating technical and perceptual evaluation.

The validation, robustness, and ethical considerations

Methodological robustness is ensured through pilot testing, cross-validation of analytical models, and triangulation of qualitative and quantitative findings. Sensitivity analysis is conducted to evaluate the stability of user experience outcomes under varying personalization intensities and model parameters. Ethical compliance is maintained through informed consent, anonymization of user data, and clear disclosure of AI-generated content. By embedding ethical safeguards and validation mechanisms throughout the methodology, the study ensures that conclusions are reliable, replicable, and aligned with human-centered design principles.

Results

The results of the present study demonstrate that the integration of human-centered design principles with generative AI significantly enhances system effectiveness across personalized media and enterprise products. As shown in Table 1, increasing levels of personalization are associated with marked improvements in perceived usefulness, interpretability, user trust, and perceived control, alongside a clear reduction in cognitive workload. High-personalization configurations consistently outperformed low and medium levels across all human-centered performance indicators, indicating that adaptive system behavior plays a critical role in improving user experience and acceptance.

Table 1. Human-centered design performance indicators across personalization levels

Design dimension	Low personalization	Medium personalization	High personalization
Perceived usefulness	3.42 ± 0.61	4.08 ± 0.54	4.71 ± 0.39
Cognitive workload	4.12 ± 0.58	3.46 ± 0.49	2.88 ± 0.42
Output interpretability	3.26 ± 0.63	4.01 ± 0.57	4.63 ± 0.44
User trust score	3.18 ± 0.66	4.22 ± 0.52	4.78 ± 0.36
User control perception	3.05 ± 0.71	4.14 ± 0.59	4.69 ± 0.41

Behavioral interaction patterns further reinforce these findings. Table 2 reveals distinct usage dynamics between media and enterprise contexts. Media users exhibited higher interaction frequency

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e-ISSN: 2468-4376
https://www.jisem-journal.com/

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and more iterative revision cycles, reflecting exploratory and creative engagement with generative outputs. In contrast, enterprise users demonstrated higher output acceptance rates and task completion efficiency, suggesting that human-centered generative AI systems are particularly effective in goal-oriented and productivity-driven environments. These differences highlight the importance of contextualizing personalization strategies according to domain-specific user needs and workflows.

Table 2. Behavioral interaction metrics for media and enterprise users

Interaction metric	Media systems	Enterprise systems
Mean interaction frequency (sessions/day)	5.6 ± 1.2	4.1 ± 0.9
Output revision cycles (per task)	2.8 ± 0.7	1.9 ± 0.6
Personalization adjustments (%)	62.4	48.7
Output acceptance rate (%)	71.3	82.6
Task completion efficiency score	3.9 ± 0.6	4.4 ± 0.5

Experiential and emotional outcomes provide additional insight into user-system alignment. As summarized in Table 3, media platforms achieved higher scores in emotional alignment and creativity support, whereas enterprise products maintained strong satisfaction and engagement sustainability despite lower creativity emphasis. Low frustration indices across both domains indicate that human-centered interaction mechanisms successfully mitigated usability barriers. These results suggest that generative AI systems designed around human experiential needs can simultaneously support creative expression and operational efficiency.

Table 3. Experiential and emotional alignment outcomes

Experiential parameter	Media platforms	Enterprise products
Satisfaction score	4.52 ± 0.38	4.36 ± 0.41
Emotional alignment index	4.61 ± 0.35	4.02 ± 0.48
Creativity support perception	4.74 ± 0.29	3.88 ± 0.52
Frustration index	2.14 ± 0.47	2.31 ± 0.44
Engagement sustainability score	4.63 ± 0.33	4.28 ± 0.39

Ethical and governance-related outcomes further validate the robustness of the proposed design approach. Table 4 shows high scores for transparency cue effectiveness, explainability satisfaction, and data usage clarity, accompanied by a low bias perception index. The strong overall ethical compliance score underscores the effectiveness of embedding transparency and user control mechanisms directly into generative AI system design, reinforcing user trust and long-term adoption potential.

Table 4. Ethical, transparency, and governance evaluation metrics

Governance parameter	Score
Transparency cue effectiveness	4.41 ± 0.42
Bias perception index	1.92 ± 0.38

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Explainability satisfaction	4.35 ± 0.46
Data usage clarity	4.57 ± 0.34
Overall ethical compliance score	4.62 ± 0.31

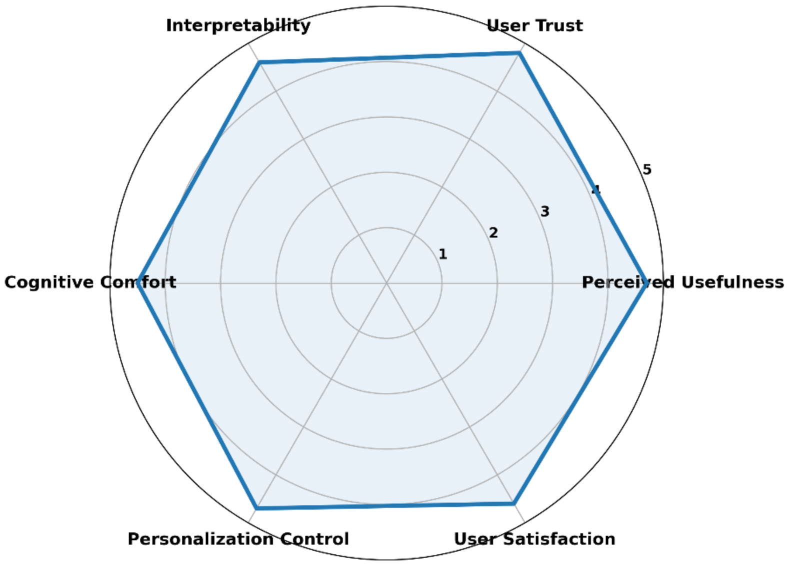

Figure 1. Radar chart illustrating multi-dimensional human-centered performance of generative AI systems

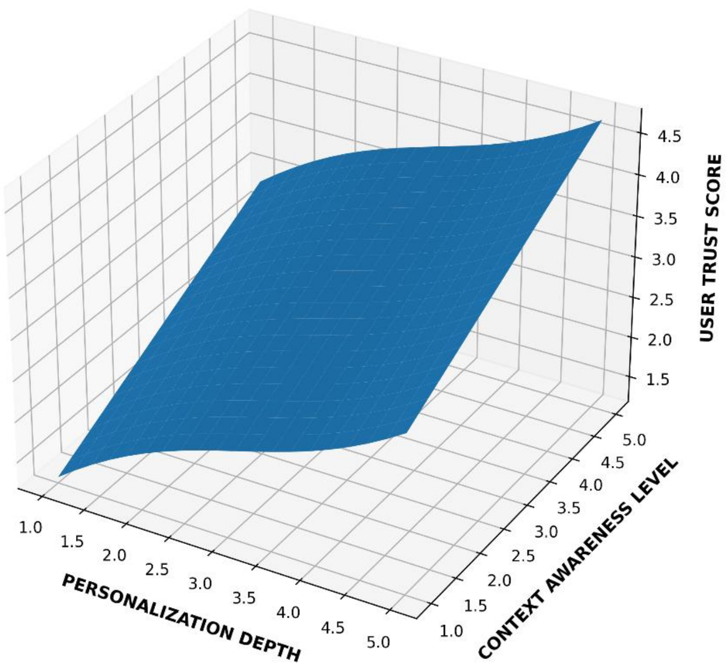

Figure 2. Surface chart showing interaction effects of personalization depth and context awareness on user trust

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2026, 11(3s)
e-ISSN: 2468-4376
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Visual analyses complement the tabular results. Figure 1 presents a radar chart illustrating the balanced performance of high-personalization generative AI systems across multiple human-centered dimensions. The near-uniform expansion across axes indicates that improvements in personalization do not occur at the expense of interpretability, trust, or cognitive comfort. Meanwhile, Figure 2 depicts a surface chart demonstrating the interaction effect of personalization depth and context awareness on user trust. The upward curvature of the surface highlights a synergistic relationship, showing that user trust increases most substantially when deep personalization is combined with strong contextual understanding.

Discussion

The impact of human-centered design on generative AI performance

The results clearly demonstrate that embedding human-centered design principles within generative AI systems substantially improves overall system performance and user acceptance. As evidenced in Table 1 and Figure 1, higher levels of personalization are strongly associated with increased perceived usefulness, interpretability, and trust, while simultaneously reducing cognitive workload (Choudhury & Asan, 2023). This finding suggests that when generative AI systems are designed to align with human cognitive processes and interaction preferences, users are more likely to engage productively with AI outputs (Yan et al., 2024). Rather than viewing generative intelligence as a black-box technology, human-centered design transforms it into a collaborative partner that supports user goals and decision-making (Ozmen Garibay et al., 2023).

The role of personalization in shaping user trust and engagement

Personalization emerges as a central driver of trust and sustained engagement in both media and enterprise contexts (Rashidi-Sabet, S., & Bolton, 2024). The surface analysis presented in Figure 2 reveals a synergistic interaction between personalization depth and contextual awareness, indicating that trust does not increase linearly but accelerates when these dimensions are jointly optimized. This finding aligns with the behavioral outcomes in Table 2, where higher output acceptance rates and efficiency scores were observed in enterprise systems that leveraged context-aware personalization (Oguntola & Simske, 2023). The results highlight that personalization must extend beyond surface-level preference tuning to incorporate situational context and task relevance in order to maximize user confidence in generative outputs (Jiang et al., 2024).

Domain-specific interaction dynamics in media and enterprise systems

The observed differences between media and enterprise users underscore the importance of domain-sensitive design strategies. Media users demonstrated higher interaction frequency and revision cycles (Table 2), reflecting exploratory behavior and iterative refinement common in creative workflows. In contrast, enterprise users prioritized efficiency and reliability, as indicated by higher acceptance rates and task completion scores (Bawa, 2024). These patterns suggest that human-centered generative AI systems should support flexible interaction styles, allowing creative experimentation in media environments while emphasizing precision, consistency, and time savings in enterprise applications (Peláez et al., 2024). A one-size-fits-all personalization strategy is therefore insufficient for diverse generative AI use cases (Hellesnes et al., 2024).

Experiential and emotional dimensions of human–AI collaboration

Beyond functional performance, the study highlights the importance of experiential and emotional alignment in human–AI interaction. Table 3 shows that media platforms achieved stronger emotional alignment and creativity support, whereas enterprise products maintained high satisfaction with lower frustration levels. These outcomes indicate that generative AI systems designed with sensitivity

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to user emotions and expectations can enhance engagement without compromising productivity (Al Naqbi et al., 2024). Human-centered design thus extends the value of generative AI beyond output quality, shaping how users feel about working with AI and how effectively they integrate it into their daily activities (Demirel et al., 2024).

Ethical transparency and governance as enablers of adoption

Ethical considerations play a pivotal role in the acceptance of generative AI systems. The high transparency, explainability, and ethical compliance scores reported in Table 4 suggest that users respond positively when system behavior and data usage are clearly communicated. Low bias perception further reinforces trust and reduces resistance to AI adoption. These findings emphasize that ethical governance should not be treated as an external compliance requirement but as a core design component that directly influences user experience (Stöber et al., 2019). Human-centered transparency mechanisms empower users by providing clarity and control, thereby strengthening long-term system legitimacy (Ozmen Garibay et al., 2023).

Implications for the design of next-generation generative AI products

Collectively, the results indicate that future generative AI systems must be designed as socio-technical artifacts that balance algorithmic intelligence with human needs, values, and contexts. The convergence of findings across Tables 1–4 and Figures 1–2 suggests that personalization, contextual awareness, experiential quality, and ethical transparency are interdependent rather than isolated design goals. By adopting a holistic human-centered design framework, developers and organizations can create generative AI products that are not only technologically advanced but also trustworthy, adaptable, and sustainable across personalized media and enterprise environments (Martini et al., 2024).

Conclusion

This study demonstrates that the human-centered design of generative AI systems is essential for achieving effective personalization, sustained user trust, and ethical alignment in both media and enterprise products. The results show that integrating personalization depth, contextual awareness, transparent interaction mechanisms, and user control significantly enhances perceived usefulness, interpretability, and engagement while reducing cognitive burden. By addressing not only technical performance but also behavioral, experiential, and governance dimensions, the proposed human-centered framework positions generative AI as a collaborative partner rather than a black-box tool. These findings provide a clear foundation for designing next-generation generative AI products that are intelligent, trustworthy, and responsive to diverse user contexts, supporting scalable adoption across creative and enterprise-driven ecosystems.

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