From Assistant to Orchestrator: A Typology of Human–AI Co-creation Logics in Generative AI–Enabled Entertainment

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Abstract

Intelligent systems increasingly participate in co-creating real-time experiential value across entertainment, education, and civic engagement. However, information systems (IS) research lacks integrative theory explaining how GenAI enables distinct modes of human–AI co-creation and how these modes relate to data ecosystem dependencies and governance requirements. Existing IS frameworks conceptualize AI primarily as a tool for efficiency, automation, or decision support in organizational task contexts, leaving experiential domains theoretically underserved. This study addresses this gap by developing a typology of human–AI co-creation in GenAI-enabled experiential contexts, drawing on a systematic literature review (SLR). We identify three ideal types, namely AI-Augmented Design, Collaborative Experience, and AI-Orchestrated Experience, each defined by distinct configurations of AI agency, data dependency, and governance intensity. Theoretically, we extend human–AI collaboration theory into experiential domains, specify data ecosystem mechanisms that activate generative affordances, and demonstrate that governance intensity scales nonlinearly with AI autonomy. Practically, the typology offers a structured framework for entertainment organizations navigating GenAI deployment decisions and informs policymakers developing differentiated AI governance standards.

Keywords

Generative AI, human-AI co-creation, experience-driven ecosystems, AI governance, entertainment

1. Introduction

Entertainment industries are undergoing transformation as generative artificial intelligence (GenAI) systems increasingly participate in the creation, adaptation, and enactment of experiences [1]. Advances in large language models (LLMs) and multimodal generative systems enable AI to produce narratives, dialogue, characters, and adaptive content in real time [2]. For example, while Disney Imagineering deploys AI backstage to generate narrative suggestions that designers refine, immersive theater platforms now deploy autonomous AI agents that improvise dialogue directly with audiences in real time—two fundamentally different co-creation logics that existing IS theory cannot distinguish. Theme parks use GenAI for adaptive storytelling [3], and mixed-reality venues orchestrate multi-user experiences through autonomous AI performers drawing on real-time behavioral data [4]. As a result, entertainment experiences are no longer fully authored by designers ex ante but emerge through ongoing human–AI interaction. This shift represents a fundamental transformation in digital business models and intelligent systems design, as entertainment organizations must now architect AI infrastructure, data ecosystems, and governance mechanisms.

This transformation challenges the core IS assumption that AI functions as a tool for efficiency, automation, or decision support within predefined human-designed workflows [5, 6]. Recent work on human–AI interaction focuses primarily on task-oriented outcomes, where AI augments human capabilities toward predefined objectives [7, 8]. These perspectives are insufficient for understanding contexts where AI systems engage directly in creative and experiential processes. Entertainment

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represents a different domain where value derives not from task completion but from immersion, emotional engagement, and meaning-making [9]. When GenAI generates narratives, improvises dialogue, or orchestrates collective experiences, it is not optimizing efficiency metrics but co-creating experiential value whose quality cannot be fully specified ex ante.

Entertainment organizations investing in GenAI face critical deployment decisions but IS research lacks integrative theory to guide them. The main question this study addresses is:

> *How do AI agency, data ecosystem requirements, and governance mechanisms combine into distinct co-creation modes in GenAI-enabled entertainment?*

This study develops a typology of human–AI co-creation in GenAI-enabled experiential contexts through a systematic literature review (SLR), making three theoretical contributions: extending human–AI collaboration theory into experiential domains, specifying data ecosystem mechanisms that activate generative affordances, and demonstrating that governance intensity scales nonlinearly with AI autonomy.

The paper proceeds as follows: Section 2 presents the theoretical background; Section 3 describes the methodology; Section 4 presents the typology; Section 5 discusses implications and limitations; Section 6 concludes.

2. Background

Following Pine and Gilmore [9], this study defines entertainment as commercially staged experiential contexts, where value derives from immersion and meaning-making. Entertainment has emerged as a critical domain for IS research, particularly as digital technologies increasingly mediate experiential value creation [10, 11]. However, existing IS research on entertainment remains fragmented across two largely disconnected streams: human–AI co-creation and experience creation in entertainment.

2.1. Human–AI Co-creation in information systems

Human–AI co-creation research examines processes where humans and AI systems jointly shape outcomes through iterative interaction [5, 7]. Extending service-dominant logic [12], this perspective recognizes AI as an active participant in value creation. However, most human–AI co-creation research focuses on task-oriented organizational contexts where value derives from efficiency, accuracy, or productivity [6]. These studies conceptualize co-creation primarily as functional collaboration toward predefined objectives. This study builds on the Hybrid Intelligence perspective [13], which examines how humans and AI complement each other's capabilities, while extending it into experiential value creation and differentiated governance configurations that task-oriented Hybrid Intelligence research has not addressed.

2.2. Generative AI and digital innovation in experience contexts

Emerging studies on GenAI in creative contexts reveal distinctive patterns. Dwivedi et al. [1] document how LLMs enable novel forms of content generation across domains, while Park et al. [2] show how AI-driven narrative adaptation creates qualitatively different gaming experiences compared to branching storylines. Xu et al. [14] demonstrate that visitors perceive AI-adapted museum exhibits as more personally relevant than static displays, suggesting GenAI activates affordances for experiential personalization unavailable with prior technologies. However, these studies treat GenAI applications individually.

3. Methodology

Because entertainment-domain GenAI co-creation represents an emerging phenomenon with no established classification framework, we created one by integrating SLR with theory-driven typology

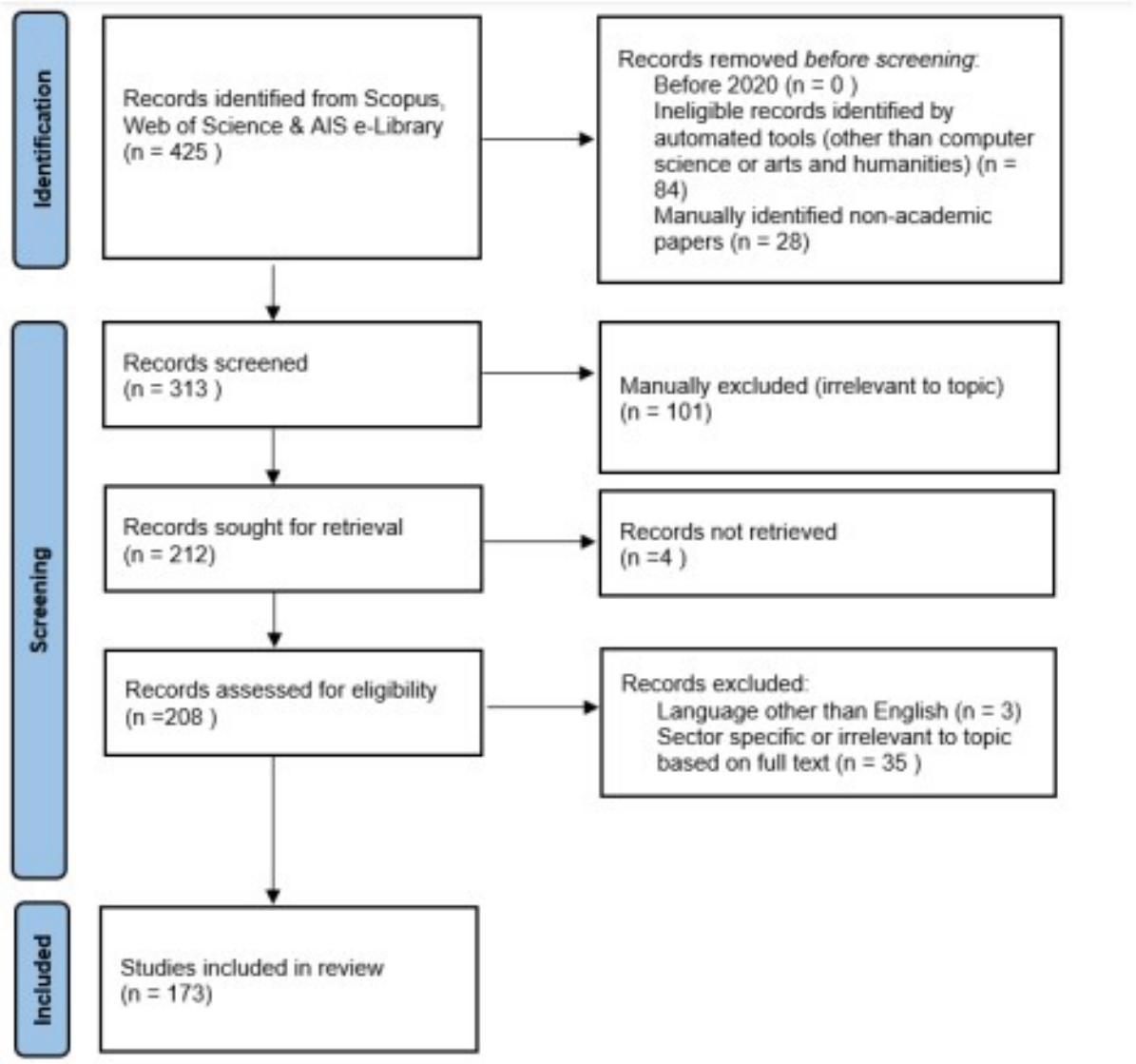

Figure 1: Systematic Literature Review Process.

development [15, 16]. We conducted an SLR following guidelines by Webster and Watson [17], encompassing identification of research objectives, selection of primary studies, quality assessment, data extraction, and synthesis. We searched AIS eLibrary, Web of Science, and Scopus using the following string applied to title, abstract, and keywords:

("generative AI" OR "GenAI" OR "large language model" OR "LLM" OR "GPT" OR "foundation model*" OR "conversational AI") AND ("entertainment" OR "experience*" OR "immersive" OR "theme park*" OR "museum*" OR "interactive installation*") AND ("co-creation" OR "human-AI interaction" OR "human-AI collaboration")*

Included studies centrally addressed generative AI or human–AI interaction in experiential or entertainment contexts, examined experience or value co-creation at organizational or platform level, provided theoretical or empirical analysis, and were published in English in peer-reviewed venues between 2020–2026. The search, executed in September 2025, yielded 425 papers after deduplication; following title and abstract screening 308 remained potentially relevant; full-text review resulted in 173 included papers, as shown in Fig. 1.

For data extraction and synthesis, we employed concept-centric coding [17] across five analytical

dimensions: (1) AI capabilities and roles in experience creation, (2) human agency and interaction modes, (3) characteristics of co-created experiences, (4) data dependencies, and (5) governance mechanisms and trust dynamics. We used thematic synthesis [18] through open, axial, and selective coding [19], with initial deductive coding grounded in service-dominant logic [12], digital innovation theory [20, 11], and affordance theory [21, 22]. Subsequent iterations allowed inductive refinement as emergent patterns revealed new conceptual distinctions, especially regarding the scaling relationship between AI agency and governance intensity. Rigor was ensured through systematic documentation, inter-coder reliability checks, and continuous validation against established theoretical frameworks.

Following Kluge [15], we identified two primary analytical dimensions, namely agency distribution (from designer-led to AI-orchestrated), grounded in service-dominant logic [12] and human–AI interaction theory [5], and generative affordances and data dependencies, grounded in digital innovation theory [20, 11]. We cross-tabulated these dimensions to group studies by shared patterns of agency distribution and infrastructure dependency, then connected agency configurations to governance requirements through multi-stage qualitative coding. We refined preliminary types by evaluating internal coherence and external distinctiveness, synthesizing three ideal types representing distinct co-creation logics, as shown in Table 1.

4. A typology of human–AI co-creation in experience-driven entertainment ecosystems

Drawing from synthesized patterns identified through our systematic review, we develop a typology of human–AI co-creation modes in entertainment. Two meta-patterns emerged across studies.

The first meta-pattern is the *agency distribution–experiential emergence tension.* As AI agency increases from assistant to collaborator to orchestrator, experiences shift from pre-designed to emergent, fundamentally altering creative control. Designer-led configurations prioritize consistency and quality but limit personalization. Collaborative configurations enable authentic responsiveness through real-time interaction but introduce unpredictability. AI-orchestrated configurations achieve sophisticated emergence at scale but require stronger governance and raise accountability questions.

The second meta-pattern is the *data dependency–generative capability scaling relationship.* Generative affordances, such as narrative generation, conversational agency, adaptive personalization, remain latent without appropriate data infrastructure. The relationship operates through three mechanisms. More specifically, *contextualization* enables AI to ground generated content in culturally relevant references and current events, *adaptation* enables real-time responsiveness to visitor behaviors and environmental conditions and *relevance* ensures generated content aligns with visitor expectations and cultural frameworks. Contextualization requires only static reference data, adaptation requires real-time contextual and behavioral data streams, while relevance demands intensive access synthesizing real-time multimodal data streams to support autonomous orchestration across multiple visitors simultaneously. These patterns form the analytical foundation for three ideal types, summarized in Table 1.

Table 1 presents the three types that define each co-creation logic. AI agency and human agency move inversely. As AI assumes more generative responsibility, human creative authority contracts from authorship to participation. Interaction timing shifts from ex ante design work to continuous real-time orchestration, reflecting the degree to which co-creation is pre-planned versus emergent. Data dependency and governance intensity escalate with AI agency, but nonlinearly. The step from Type II to Type III represents a substantially larger increase in both infrastructure requirements and governance complexity than the step from Type I to Type II. Organizations that treat the transition to Type III as a linear extension of Type II will systematically underinvest in both data infrastructure and accountability mechanisms.

Type I, namely AI-Augmented Design represents a designer-led creation logic in which generative AI supports human creators during design but does not engage directly with visitors. AI functions strictly as an assistant, offering narrative suggestions, generating dialogue variations, or producing design alternatives that human designers evaluate and refine [23]. Human designers retain complete

Table 1
Typology of Human–AI Co-creation Modes in GenAI-Enabled Entertainment

Dimension	Type I: AI-Augmented Design	Type II: Collaborative Experience	Type III: AI-Orchestrated Experience
Studies	69	56	48
Primary logic	Designer-led creation	Shared real-time authorship	AI-driven emergence
AI agency	Low (assistant)	Medium (collaborator)	High (orchestrator)
Human agency	High (author)	Medium (co-author)	Low (participant)
Interaction timing	Ex ante (design phase)	Real-time (during experience)	Continuous (adaptive orchestration)
Data dependency	Low (reference data)	Medium (contextual data)	High (real-time multimodal)
Governance intensity	Low (designer oversight)	Medium (interaction protocols)	High (algorithmic accountability)
Examples	AI scriptwriting; narrative suggestion systems	Interactive museum exhibits; TeamLab installations	Autonomous VR performers; AI-orchestrated immersive theater

creative authority, posing problems, evaluating AI outputs, and integrating selected elements into coherent wholes [24]. This mirrors traditional computer-aided design where tools expand possibilities without assuming creative agency. Experiences delivered to visitors are pre-authored and fixed: once design is complete, visitors consume predetermined content [25]. Co-creation intensity is low because AI contributes only to design processes, not experience enactment. Data dependency is low; systems draw on reference data such as cultural databases, genre corpora, and design patterns, without requiring real-time access to visitor data or environmental conditions. Governance remains minimal and organizationally contained, such as design reviews, quality assurance, artistic approval, with AI-specific governance focused primarily on intellectual property. Notable examples include Disney Imagineering's AI-assisted scriptwriting tools that generate narrative suggestions for attractions which designers refine [3], and museums employing AI systems proposing exhibition narrative flows that curators evaluate against educational objectives [14].

Type II, which is Collaborative Experience, brings AI directly into visitor-facing experiences, creating a shared authorship logic through real-time human–AI interaction. AI functions as a collaborator, improvising dialogue, adapting narratives, or personalizing content in response to visitor input during experience enactment. Unlike Type I's suggestion-and-selection dynamic, Type II AI actively generates content in real time, interpreting visitor behaviors and producing contextually appropriate responses. However, AI agency remains bounded by interaction protocols and design parameters [25]. Human visitors shift from author to co-author, becoming active participants whose choices meaningfully shape experience trajectories; co-creation intensity is medium, with visitors typically initiating and AI responding within boundaries [26]. Data dependency increases to moderate levels: systems access social media, behavioral data (movement patterns, interaction duration), and environmental data (time, weather, crowd density) to enable real-time adaptation [27], requiring affordances such as adaptive personalization and conversational agency. Governance complexity increases correspondingly, requiring mechanisms spanning interaction protocols, transparency, visitor control, and live quality monitoring [28, 27]. Examples include museum exhibits deploying conversational AI that tailors explanations to visitor expertise levels [28], and adaptive games generating story branches responsive to player moral choices [29, 2].

Finally, Type III, AI-Orchestrated Experience represents an autonomous orchestration logic where AI manages complex multi-agent scenarios with minimal direct human control. AI functions

as performer and orchestrator, managing narrative flow, coordinating multiple agents, and adapting holistically to emergent conditions without real-time human approval. Type III synthesizes patterns across multiple visitors, optimizes collective experience trajectories, and proactively generates events. Human visitors become primarily participants who influence experiences through aggregate behaviors but cannot meaningfully steer trajectories through individual choices [30]. Designers establish objectives and constraints ex ante but do not intervene during enactment, transitioning from authoring content to authoring systems; experiences become largely emergent, arising from AI interpretation of contextual conditions [31]. Data dependency reaches highest intensity, with systems requiring continuous access to visitor behavioral traces, social media streams, environmental sensors, and historical interaction data [31, 4]. Type III typically integrates 10–15 distinct data streams, enabling continuous narrative generation, complex multi-party interactions, and simultaneous individual and collective personalization. Governance reaches its highest intensity, requiring mechanisms from pre-deployment testing and real-time monitoring through to accountability structures and continuous auditing, reflecting that autonomous orchestration cannot be governed through one-time oversight alone [32, 33]. Notable examples include entertainment platforms deploying autonomous AI performers orchestrating multi-user experiences based on aggregated player behaviors [1], and immersive theaters using AI agents coordinating narrative timing and character behaviors based on real-time audience response patterns.

The shift from authoring content to authoring systems carries significant ethical implications that distinguish Type III from lower types. When AI orchestrates experiences autonomously, designers bear responsibility for behavioral outcomes they cannot fully anticipate. Unlike Type I, where designers review every AI output before visitor exposure, or Type II, where AI operates within bounded interaction protocols, Type III places designers in an ex ante governance position: they specify objectives and constraints but cannot intervene as the system generates emergent experience trajectories. This creates an accountability gap between the locus of design decisions and the locus of experiential consequences. Visitors in Type III environments may be unaware that their aggregate behavioral data is shaping the experience in real time, raising transparency obligations that standard informed consent mechanisms do not address. Governance frameworks for Type III must therefore extend beyond algorithmic accountability to include visitor awareness mechanisms, data minimization requirements, and intervention triggers that allow human operators to override autonomous orchestration when emergent behavior diverges from designer intent.

In practice, organizations rarely occupy a single type exclusively. A theme park may deploy Type I AI for attraction scriptwriting while simultaneously running Type II conversational exhibits in its museums. The typology therefore functions as a diagnostic tool applied at the level of individual deployments. Transitions between types require organizations to develop three capabilities before moving up: the data infrastructure to handle higher-volume streams, governance mechanisms suited to higher AI autonomy, and sufficient visitor familiarity with AI creative roles. Organizations that attempt Type III deployment without Type II governance experience consistently encounter legitimacy failures, as the accountability mechanisms required for autonomous orchestration cannot be improvised retroactively. A practical implication is that Type II deployment serves as a necessary governance apprenticeship for organizations targeting Type III, building the monitoring infrastructure and intervention protocols that autonomous orchestration requires at scale.

5. Discussion

This study addresses a gap in IS research on how generative AI transforms value creation in experiential domains.

5.1. Theoretical contributions

Our study makes three primary theoretical contributions. First, we contribute to the emerging literature on human–AI collaboration by extending it beyond task-oriented contexts into experiential domains where value derives from immersion and meaning-making [7, 6]. Although the three types

may superficially resemble automation–augmentation–autonomy distinctions, our typology differs fundamentally by theorizing co-creation as an experiential phenomenon. Our typology thus extends beyond degree-of-automation models by integrating agency, infrastructure dependency, and trust mechanisms into a unified explanatory framework.

Second, we contribute to digital innovation theory by specifying mechanisms through which data ecosystems activate generative affordances in experiential contexts [20, 11]. Our framework reveals that data ecosystems function as experiential infrastructure—not merely input resources but constitutive elements that determine what AI can generate and how experiences emerge. This moves beyond treating data ecosystems as undifferentiated resources to theorizing how their characteristics shape innovation outcomes.

Third, we contribute to governance research by demonstrating that governance requirements scale nonlinearly [34, 35]. Governance here does two things. It builds the visitor trust that makes intensive co-creation possible, and it constrains AI behavior within ranges that visitors find acceptable. Organizations that constrain AI with excessive oversight designed for autonomous systems sacrifice personalization unnecessarily, while those applying minimal oversight to autonomous AI risk legitimacy failures.

5.2. Practical implications

For practitioners, our typology provides a structured framework for matching GenAI implementation approaches to organizational capabilities and visitor expectations. Organizations with limited data infrastructure should focus on Type I implementations that leverage GenAI for creative augmentation without requiring real-time data access. Those with moderate data capabilities and willingness to implement interaction protocols can pursue Type II collaborative experiences. Organizations with extensive data infrastructure, technical expertise, and resources for comprehensive governance can explore Type III orchestration, but must recognize that governance requirements intensify substantially.

For policymakers, our findings suggest that one-size-fits-all approaches are inadequate. Type I implementations require primarily intellectual property protections; Type II demands visitor consent and transparency mechanisms; Type III necessitates algorithmic accountability and continuous auditing. Policy interventions that impose Type III governance requirements on all GenAI applications risk stifling innovation in lower-risk Type I and II implementations. Beyond deployment matching, the typology offers a readiness assessment function. Organizations can audit their current position by mapping existing infrastructure against the data dependency row of Table 1 and mapping existing oversight mechanisms against the governance intensity row. Misalignment between these two dimensions identifies specific investment gaps. This audit logic transforms the typology from a descriptive classification into a prescriptive planning tool, enabling organizations to sequence capability investments toward their target co-creation mode.

5.3. Limitations and future research

First, the typology derives from literature synthesis. Empirical validation through comparative case studies examining real organizations across types remains the critical next step. Particularly valuable would be longitudinal studies tracking organizations as they transition between types to establish whether the typology's ideal-type configurations represent stable equilibria or way stations in evolutionary trajectories. Validation studies should also examine failure cases, documenting organizations that attempted Type III deployment without adequate governance readiness, to test the nonlinear scaling relationship this study identifies theoretically. Second, the framework does not address how organizations orchestrate transitions between types or what capabilities beyond technical infrastructure enable successful Type III implementation. Third, cultural variation in visitor expectations and governance norms is acknowledged but not theorized, and cross-cultural research should examine whether types exhibit universal applicability or cultural moderation.

6. Conclusion

This study reconceptualizes entertainment as an experience-driven AI ecosystem organized around human–AI co-creation, advancing IS theory through three contributions: a theory-driven typology distinguishing AI-augmented design, collaborative experience, and AI-orchestrated modes that differ systematically in agency distribution and governance requirements; and a mechanism-based framework explaining how data ecosystems enable generative affordances through contextualization, adaptation, and relevance mechanisms. By demonstrating that effective GenAI implementation requires alignment between AI agency, data infrastructure, and governance, this research provides both theoretical foundations for cumulative scholarship and a structured framework for practitioners navigating deployment decisions. While developed in entertainment contexts, the theoretical insights transfer to other experiential domains including education, healthcare, and civic participation where AI increasingly shapes human engagement.

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Declaration on Generative AI

The author(s) have not used Generative AI tools to adjust the text's language and tone.

References

[1] Y. K. Dwivedi, et al., Opinion paper: "So what if ChatGPT wrote it?" Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy, International Journal of Information Management 71 (2023) 102642.

[2] J. Park, Y. Cheong, B. Bae, A character-centric interactive fiction generation system, in: 8th International Workshop on Computational Models of Narrative (CMN 2025), 2025.

[3] F. F.-H. Nah, R. Zheng, J. Cai, K. Siau, L. Chen, Generative AI and ChatGPT: Applications, challenges, and AI-human collaboration, Journal of Information Technology Case and Application Research 25 (2023) 277–304.

[4] D. Platnick, M. Gruener, M. Alirezaie, K. Larson, D. J. Newman, H. Rahnama, Perspective-aware AI in extended reality, in: International Conference on Extended Reality, Springer Nature Switzerland, Cham, 2025, pp. 85–97.

[5] S. Faraj, S. Pachidi, K. Sayegh, Working and organizing in the age of the learning algorithm, Information and Organization 28 (2018) 62–70.

[6] S. Raisch, S. Krakowski, Artificial intelligence and management: The automation–augmentation paradox, Academy of Management Review 46 (2021) 192–210.

[7] S. Lebovitz, N. Levina, H. Lifshitz-Assaf, Is AI ground truth really true? The dangers of training and evaluating AI tools based on experts' know-what, MIS Quarterly 45 (2021) 1501–1525.

[8] A. Przegalinska, T. Triantoro, Converging Minds: The Creative Potential of Collaborative AI, Routledge, 2024. doi:10.4324/9781032626871.

[9] B. J. Pine, J. H. Gilmore, Welcome to the experience economy, Harvard Business Review 76 (1998) 97–105.

[10] J. Huang, J. Back, R. Oppermann, A context-aware guide for the museum: Guidelines for design and evaluation, World Wide Web 16 (2013) 1–27.

[11] S. Nambisan, K. Lyytinen, A. Majchrzak, M. Song, Digital innovation management: Reinventing innovation management research in a digital world, MIS Quarterly 41 (2017) 223–238.

[12] S. L. Vargo, R. F. Lusch, Service-dominant logic: Continuing the evolution, Journal of the Academy of Marketing Science 36 (2008) 1–10.

[13] M. Petrescu, A. S. Krishen, Hybrid intelligence: human–AI collaboration in marketing analytics, Journal of Marketing Analytics 11 (2023) 263–274. doi:10.1057/s41270-023-00245-3.
[14] Y. Xu, et al., How generative AI shapes user perceived value and adoption intention in digital museum experiences, Journal of Cultural Heritage Management and Sustainable Development (2025).
[15] S. Kluge, Empirically grounded construction of types and typologies in qualitative social research, Forum Qualitative Sozialforschung / Forum: Qualitative Social Research 1 (2000) Article 14. doi:10.17169/fqs-1.1.1124.
[16] R. C. Nickerson, U. Varshney, J. Muntermann, A method for taxonomy development and its application in information systems, European Journal of Information Systems 22 (2013) 336–359.
[17] J. Webster, R. T. Watson, Analyzing the past to prepare for the future: Writing a literature review, MIS Quarterly 26 (2002) xiii–xxiii.
[18] J. Thomas, A. Harden, Methods for the thematic synthesis of qualitative research in systematic reviews, BMC Medical Research Methodology 8 (2008) 45. doi:10.1186/1471-2288-8-45.
[19] J. Corbin, A. Strauss, Basics of Qualitative Research: Techniques and Procedures for Developing Grounded Theory, 4th ed., Sage Publications, 2015.
[20] Y. Yoo, O. Henfridsson, K. Lyytinen, Research commentary—The new organizing logic of digital innovation: An agenda for information systems research, Information Systems Research 21 (2010) 724–735.
[21] J. J. Gibson, The Ecological Approach to Visual Perception, Houghton Mifflin, 1979.
[22] D. A. Norman, The Psychology of Everyday Things, Basic Books, 1988.
[23] S. Pansoni, E. Beck, S. Tiribelli, On the need of a decolonized AI ethics and governance framework for human-GenAI cooperation in the art sector: A roadmap, in: International Workshop on Explainable, Trustworthy, and Responsible AI and Multi-Agent Systems, Springer Nature Switzerland, Cham, 2025, pp. 191–210.
[24] R. Louie, A. Cohen, C. Z. A. Huang, M. Terry, C. J. Cai, Cococo: AI-Steering tools for music novices co-creating with generative models, in: HAI-GEN+ user2agent@IUI, 2020.
[25] V. N. Antony, C. M. Huang, ID. 8: Co-creating visual stories with generative AI, ACM Transactions on Interactive Intelligent Systems 14 (2025) 1–29.
[26] M. Takaffoli, S. Li, V. Mäkelä, Generative AI in user experience design and research: How do UX practitioners, teams, and companies use GenAI in industry?, in: Proceedings of the 2024 ACM Designing Interactive Systems Conference, 2024, pp. 1579–1593.
[27] T. Luther, J. Kimmerle, U. Cress, Teaming up with an AI: Exploring human–AI collaboration in a writing scenario with ChatGPT, AI 5 (2024) 1357–1376.
[28] M. H. Jarrahi, D. Askay, A. Eshraghi, P. Smith, Artificial intelligence and knowledge management: A partnership between human and AI, Business Horizons 66 (2023) 87–99.
[29] D. Yang, E. Kleinman, G. M. Troiano, E. Tochilnikova, C. Harteveld, Snake story: Exploring game mechanics for mixed-initiative co-creative storytelling games, in: Proceedings of the 19th International Conference on the Foundations of Digital Games, 2024, pp. 1–11.
[30] T. Wissigkeit, D. Lope-Nicholls, C. Stindl, I. A. Iurgel, Exploring phantasmagorical game design: Integrating anomalous behaviour of AI and player into conversational AI-native games, in: International Conference on Design, Learning, and Innovation, Springer Nature Switzerland, Cham, 2024, pp. 120–135.
[31] J. Rezwana, M. L. Maher, An exploration of mental models of AI in human–AI co-creativity: A framework and insights, ACM Transactions on Interactive Intelligent Systems 15 (2025) 1–26.
[32] Q. Wan, X. Feng, Y. Bei, Z. Gao, Z. Lu, Metamorpheus: Interactive, affective, and creative dream narration through metaphorical visual storytelling, in: Proceedings of the 2024 CHI Conference on Human Factors in Computing Systems, 2024, pp. 1–16.
[33] A. Rozo-Torres, C. J. Latorre-Rojas, W. J. Sarmiento, From trends to experiences: Co-creation with generative artificial intelligence in developing interactive multimedia applications, CLEI Electronic Journal 27 (2024) 6–1.
[34] B. Mittelstadt, Principles alone cannot guarantee ethical AI, Nature Machine Intelligence 1 (2019)

501–507.
[35] A. Jobin, M. Ienca, E. Vayena, The global landscape of AI ethics guidelines, Nature Machine Intelligence 1 (2019) 389–399. doi:10.1038/s42256-019-0088-2.