Chapter 6:

Generative AI as a Co-Creator in Innovation Management

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doi: https://doi.org/10.66414/mls.978-1-0666009-1-5_6

Abstract

Generative artificial intelligence (GenAI) is reshaping innovation management by moving beyond its conventional role as a technological tool toward becoming an active participant in creative and decision-making processes. This chapter examines how GenAI can function as a co-creator across the innovation process and explores the complementary roles of human and artificial intelligence in generating meaningful innovation outcomes. Adopting a structured integrative literature review approach, the study synthesizes recent research on GenAI-enabled innovation through thematic analysis and conceptual synthesis. The findings indicate that GenAI contributes across multiple stages of innovation, including opportunity recognition, idea generation and evaluation, product and service development, business model innovation, commercialization, and organizational innovation. Its primary strengths lie in rapid content generation, knowledge synthesis, recombination, scenario development, and iterative refinement, whereas human contributors remain central to problem framing, contextual interpretation, strategic and ethical judgment, validation, and accountability. Building on these complementary capabilities, the chapter proposes the Human–GenAI Innovation Co-Creation Framework, which conceptualizes innovation as an iterative cycle of framing, generating, evaluating, refining, validating, and experimenting. The analysis further identifies hallucination, bias and idea homogenization, intellectual property concerns, human over-reliance, AI literacy, and organizational governance as important boundary conditions shaping the effectiveness of co-creation. Overall, the chapter argues that the transformative potential of GenAI in innovation management lies not in replacing human innovators but in designing organizational processes that deliberately combine human judgment and creativity with GenAI's generative and synthetic capabilities.

Keywords: generative artificial intelligence, innovation management, human–AI co-creation, human–AI collaboration, innovation process

1. Introduction

Innovation management has always been a discipline defined by the effort to organize uncertainty. Firms invest in structured processes for recognizing opportunities, generating ideas, evaluating alternatives, developing concepts, and bringing new products, services, and business models to market, precisely because the underlying activities are creative, ambiguous, and resistant to routine (Vocke & Bauer, 2020). Over the past two decades, digital technologies have progressively reshaped these processes: computer-aided design tools accelerated prototyping, digital platforms opened innovation to external contributors, and analytics systems supported evidence-based decision-making. Artificial intelligence extended this trajectory by adding predictive and classificatory capabilities—forecasting demand, screening patents, and flagging anomalies—without directly participating in the generative, judgment-intensive core of innovation work.

The emergence of generative artificial intelligence (GenAI) marks a qualitatively different moment in this trajectory. Unlike earlier digital tools, GenAI systems can produce novel textual, visual, and structural content on demand, at a pace and scale that was previously unattainable (Girotra et al., 2023). This capability arrives at a time when organizations already face intensifying pressure to innovate faster, under conditions of greater market volatility and information overload (Salminen et al., 2024). Firms are being asked to generate and evaluate a larger number of ideas, in shorter cycles, while maintaining—or improving—the quality, novelty, and feasibility of the outcomes. It is in this context that GenAI has moved from the periphery of innovation management research to its center.

Generative AI refers to a class of machine learning systems—most prominently large language models (LLMs) and increasingly multimodal foundation models—capable of producing coherent text, images, code, and structured design artifacts in response to natural-language prompts (Altun et al., 2026). These systems are trained on vast corpora and learn statistical regularities that allow them to recombine and synthesize existing knowledge into new configurations, rather than simply retrieving or

classifying pre-existing content. This is the crucial distinction between traditional AI and generative AI: whereas traditional AI applications in innovation management have historically supported prediction, optimization, and classification tasks, generative systems produce original outputs—drafts, alternatives, scenarios, and prototypes—that can be directly inserted into creative and decision-making workflows (Mariani & Dwivedi, 2024).

The practical accessibility of tools such as ChatGPT, and comparable systems for image, code, and design generation, has been a decisive factor in this shift. Because these interfaces require no specialized technical training, GenAI has diffused rapidly not only into research and development functions but into marketing, product management, and strategic planning more broadly (Kanbach et al., 2024). This combination of generative capability and ease of use is what distinguishes the current moment from earlier waves of AI adoption in innovation contexts.

A useful way to characterize this shift is to trace an evolving continuum of roles that AI systems occupy in innovation work. At one end, AI functions purely as a tool: a fixed-purpose instrument that executes a specific, narrowly defined operation—such as running a regression or automating a repetitive task—with no interpretive latitude. Moving along the continuum, AI can act as an assistant, handling well-specified sub-tasks (such as drafting a first version of a document) under close human direction. Further along, AI becomes a collaborator, participating iteratively in a shared task and adjusting its outputs in response to human feedback within a bounded exchange. Figure 1 summarizes this continuum.

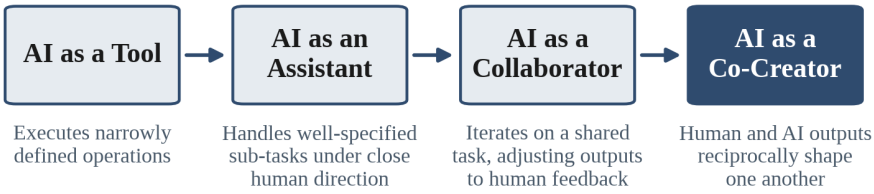


Figure 1. Evolution of AI's role in innovation

The concept explored throughout this chapter occupies the far end of this continuum: AI as a co-creator. In this role, GenAI does not merely execute instructions or await approval; its outputs actively shape the direction of the human's subsequent thinking, and the human's responses in turn reshape the AI's next contribution, in a mutually influencing cycle (Jiang & Wagner, 2026). Co-creation, in this sense, is defined not by the sophistication of the underlying model but by the structure of the interaction: it is a process in which neither party's contribution can be fully understood in isolation from the other's. This conceptualization is developed further in Section 5, where the distinction between human-in-the-loop supervision and genuine co-creation is examined in detail.

This chapter examines how Generative AI can function as a co-creator throughout the innovation management process, synthesizing the rapidly growing body of research on GenAI-enabled ideation, evaluation, development, and commercialization. It is guided by one overarching research question and three supporting questions:

Main RQ: How can Generative AI function as a co-creator throughout the innovation management process?

RQ1: What roles does Generative AI play across different stages of the innovation process?

RQ2: How does human–AI collaboration contribute to innovation outcomes?

RQ3: What challenges and boundary conditions influence Generative AI-enabled innovation co-creation?

The chapter's central argument is that Generative AI is evolving from a technological tool into an active co-creator that participates in the generation, development, evaluation, and commercialization of innovation, while human expertise, judgment, and governance remain essential for achieving meaningful innovation outcomes. The remainder of the chapter develops this argument through a review of conceptual foundations (Section 2), a description of the methodological approach (Section 3), a stage-by-stage analysis of GenAI's contributions across the

innovation process (Section 4), an examination of the co-creation dynamic itself (Section 5), a discussion of challenges and boundary conditions (Section 6), a proposed conceptual framework (Section 7), a discussion of theoretical and managerial implications (Section 8), and a concluding synthesis (Section 9).

2. Conceptual Foundations

2.1. Innovation Management

Innovation management is the deliberate organization of the activities through which firms identify opportunities and convert them into new or improved products, services, processes, business models, or organizational arrangements. Although accounts of the innovation process vary in granularity, most converge on a broadly sequential—if in practice iterative and recursive—set of stages: opportunity recognition, idea generation, idea evaluation, and development through to commercialization. To keep the analysis consistent, this chapter uses a single seven-part classification of the innovation process throughout (Section 4, Figure 2, and Table 2): opportunity recognition, idea generation, idea evaluation, product and service development, business model innovation, commercialization, and organizational innovation. Experimentation is not treated as a separate stage: prototyping and experimentation activities are discussed as part of product and service development (Section 4.4), and experimentation appears as the final step of the co-creation cycle described in Section 5.2. Business model innovation and organizational innovation, which extend the focus from products and services to how firms create and capture value and organize themselves, are included as stages of the same classification rather than as parallel categories. Innovation management, as a field, is concerned with designing the structures, capabilities, and decision rules that allow organizations to move through these stages efficiently while managing the inherent uncertainty of creative and market outcomes. It encompasses not only product innovation but also service innovation, business model innovation, and organizational or process innovation, each of which

follows a related but distinct logic. Because each of these activities depends on generating, combining, and evaluating information under uncertainty, innovation management has long been understood as a knowledge-intensive discipline—one to which GenAI, as a knowledge-synthesizing and content-generating technology, is particularly well suited to contribute.

2.2. Generative AI

For the purposes of this chapter, Generative AI is understood as a category of foundation models—including large language models and increasingly multimodal systems—capable of generating novel content across text, image, audio, and code modalities in response to natural-language input. Three capabilities are of particular relevance to innovation management. First, content generation: the ability to produce drafts of text, visual concepts, or code that can serve as raw material for further human refinement. Second, knowledge synthesis and recombination: the ability to draw on patterns learned from large and heterogeneous corpora and recombine them into configurations that may not previously have been explicitly articulated. Third, idea and scenario generation: the ability to produce multiple divergent alternatives—ideas, personas, future scenarios, or design variants—rapidly and at low marginal cost (Gindert & Müller, 2024; Girotra et al., 2023). This chapter deliberately avoids extended discussion of model architecture, training methodology, or the technical mechanics of transformer-based systems, since these details, while foundational to computer science, are largely orthogonal to the question of how GenAI functions within innovation management practice.

2.3. Human–AI Collaboration

A further conceptual foundation concerns the nature of human–AI interaction. The literature on human–AI collaboration distinguishes several related but distinct configurations. AI augmentation refers to the use of AI systems to extend human cognitive or perceptual capacity, without necessarily involving iterative exchange. AI-assisted decision-

making describes configurations in which AI provides recommendations or analyses that a human then incorporates into a decision, typically in a single pass. Human-in-the-loop approaches designate systems in which AI performs a task largely autonomously, subject to human supervision, correction, or approval at defined checkpoints. Co-creation, by contrast, is the configuration in which human and AI outputs continuously and reciprocally shape one another over multiple iterations, such that the resulting artifact cannot be attributed cleanly to either party alone (Kadenhe et al., 2025). This distinction between assistance and co-creation is conceptually important because it has direct implications for how organizations should design workflows, allocate responsibility, and evaluate innovation outcomes—implications that are developed at length in Section 5.

3. Methodology

3.1. Research Design

This chapter adopts a structured integrative literature review approach, combining thematic analysis with conceptual synthesis. The purpose of this approach is not to provide a statistically exhaustive account of the emerging GenAI literature, but to organize and interpret a rapidly developing and methodologically heterogeneous body of research in order to identify recurring patterns in human–GenAI collaboration across the innovation process. The chapter does not follow a full systematic review protocol (such as a pre-registered protocol with formal quality appraisal of each study); instead, the structured search and selection procedure described in Sections 3.2 and 3.3 is intended to make the identification of the relevant body of research transparent and traceable. Within this design, the thematic analysis component organizes that literature into recurring conceptual categories, and the conceptual synthesis component integrates these categories into the Human–GenAI Innovation Co-Creation Framework presented in Section 7. This combination of methods is appropriate for a topic such as this one, where the underlying phenomenon—GenAI-enabled innovation—is recent,

methodologically heterogeneous, and dispersed across several adjacent literatures (innovation management, human–computer interaction, creativity research, and information systems), such that a purely quantitative bibliometric approach would understate the conceptual richness of the field, while a purely narrative review would risk insufficient transparency.

3.2. Literature Search Strategy

The literature search was conducted in Scopus and Web of Science, given their broad coverage of peer-reviewed research in management, information systems, human–computer interaction, and related fields. The searches covered publications from 2020 to Jume of 2026. Two search strings were used as the final search strategy. The core string combined terms for generative AI with terms for innovation and co-creation:

("generative AI" OR "generative artificial intelligence" OR "large language model" OR "LLM") AND ("innovation management" OR "innovation process*" OR "innovation" OR "co-creation")

A second, complementary string focusing on human–AI interaction was run to capture studies on collaboration and co-creation that the core string might not retrieve in combined form.

("human-AI collaboration" OR "human-AI interaction" OR "AI co-creation")

Studies were included if they (a) were peer-reviewed journal articles, conference proceedings, or other emerging scholarly contributions (including preprints and working papers where no published version was available); (b) examined generative AI or large language models in relation to innovation activities, innovation management, or human–AI collaboration and co-creation; and (c) were published between 2020 and 2026, written in English. Studies were excluded if they did not meaningfully address these themes, and duplicate entries of same studies excluded.

3.3. Screening and Selection

The literature selection process was guided by thematic relevance, publication period, and the substantive contribution of each study to the understanding of Generative AI, innovation management, and human–AI collaboration. Particular attention was given to studies that examined the use of GenAI in innovation-related activities, including idea generation, evaluation, product and service development, decision support, organizational innovation, and business model innovation. The literature considered in this chapter covers recent contributions published primarily between 2020 and 2026 across fields such as innovation management, human–computer interaction, information systems, and related interdisciplinary domains.

Because this chapter follows a structured integrative literature review rather than a full systematic review protocol, the literature was organized to support the conceptual purpose of the chapter. Studies were therefore examined for their relevance to the central research questions and grouped according to recurring themes and analytical categories. The selection process emphasized peer-reviewed academic articles as well as relevant conference proceedings and emerging scholarly contributions where they provided substantive insights into GenAI-enabled innovation and human–AI collaboration. Publications that did not meaningfully address these themes were excluded from the analytical scope.

The resulting body of literature was not intended to constitute a statistically exhaustive sample of the entire GenAI research landscape. Instead, it served as the conceptual and empirical foundation for identifying recurring patterns, relationships, and tensions in the literature. Accordingly, the analysis focuses on the roles assumed by GenAI across different stages of innovation, the mechanisms through which human–AI collaboration may contribute to innovation outcomes, and the organizational and ethical conditions that may constrain such collaboration.

3.4. Thematic Analysis

The thematic analysis organizes the selected literature into eleven recurring codes: idea generation, idea evaluation, knowledge creation, product development, decision support, business model innovation, organizational innovation, creativity augmentation, human role, AI role, and risks and governance. These codes are not mutually exclusive, as individual studies may contribute to several themes simultaneously. Rather, they provide an analytical structure for synthesizing the literature and identifying recurring patterns across studies. [[The codes were developed through a combination of deductive and inductive steps. Codes that correspond to stages of the innovation process (idea generation, idea evaluation, product development, business model innovation, and organizational innovation) were defined in advance on the basis of the innovation management literature summarized in Section 2.1, whereas the remaining codes (knowledge creation, decision support, creativity augmentation, human role, AI role, and risks and governance) were derived from the reviewed studies as recurring themes emerged during reading. Each study was read in full and assigned to one or more codes according to the contributions reported in its findings; the coded studies were then grouped by theme and mapped onto the innovation stages discussed in Section 4 and onto the co-creation and boundary-condition themes discussed in Sections 5 and 6.]] In particular, the codes provide the organizing logic for Section 4, which maps the identified themes onto different stages of the innovation process, and Section 6, which brings together the risk- and governance-related themes to examine the boundary conditions of GenAI-enabled innovation and human–AI co-creation.

4. Generative AI Across the Innovation Process

This section examines GenAI's contribution along the single seven-part classification of the innovation process introduced in Section 2.1: opportunity recognition, idea generation, idea evaluation, product and service development, business model innovation, commercialization, and organizational innovation (Figure 2). The same classification structures

Table 2, which summarizes the stage-specific roles, representative activities, and illustrative outcomes at the end of this section. As noted in Section 2.1, these stages are treated as iterative and recursive rather than strictly linear.

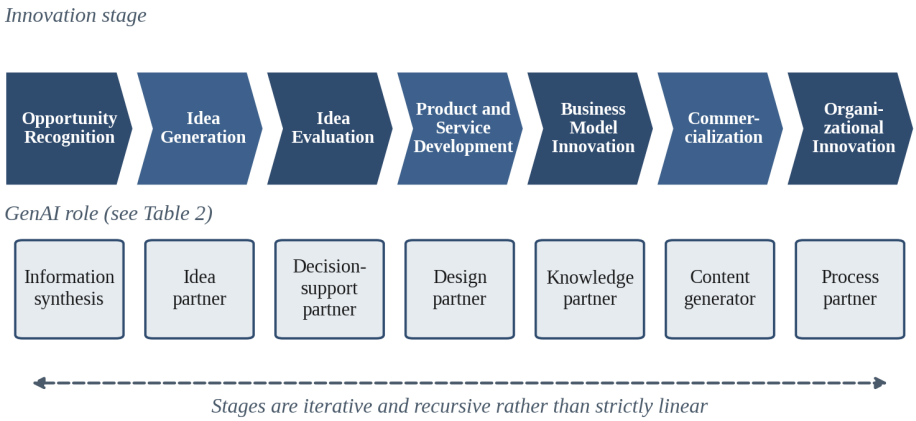


Figure 2. Generative AI across the innovation management process

4.1. Opportunity Recognition

The earliest stage of the innovation process involves identifying gaps, unmet needs, or emerging possibilities in the environment—monitoring market trends, customer needs, emerging technologies, competitor activity, and weak signals that may indicate a shift worth pursuing. GenAI's contribution here is primarily one of information synthesis: large language models can rapidly summarize and cross-reference large volumes of unstructured text—reports, reviews, forum discussions, and technical literature—surfacing patterns that would otherwise require extensive manual analysis. However, the framing of a problem as worth pursuing, and the judgment as to which weak signal is strategically significant, remains a distinctly human activity. This division of labor—AI information synthesis paired with human problem framing—recurs throughout the innovation process and is a first indication of the complementarity theme developed more fully in Section 5.

4.2. Idea Generation

Idea generation is the stage at which GenAI's contribution has been most extensively studied to date. Empirical work comparing GenAI-generated ideas with those produced by trained human participants has found that large language models can generate a substantially higher volume of ideas, more quickly and at lower cost, and that a meaningful share of the highest-quality ideas in pooled human–AI samples originate from the AI system rather than from human participants (Girotra et al., 2023). Related field-experimental work confirms that GenAI-augmented teams can produce higher-quality ideas in less time, while also reporting ancillary benefits such as improved knowledge exchange, greater engagement, and increased idea diversity (Gindert & Müller, 2024). At the same time, this literature is careful to separate idea quantity from idea quality: rapid generation of many alternatives does not by itself guarantee that any given idea is useful or original. Steppe et al. (2025) show that prompting a language model to generate ideas does not, on its own, augment creativity; rather, the creativity-enhancing effect emerges through iterative perspective-taking and refinement of the AI's initial output, which increases the comprehensiveness of the idea set and helps identify the ideas that are both novel and useful. In a related interview-based study, Quiel et al. (2026) similarly find that GenAI reshapes organizational ideation by expanding the sources from which ideas can be drawn, while the ultimate creative contribution continues to depend on how organizations structure the adoption and use of these tools. Taken together, this body of work suggests that GenAI expands the searchable space of possible ideas and lowers the cost of exploring it, but that the translation of this expanded space into innovation value depends on subsequent human evaluative and developmental work.

4.3. Idea Evaluation

Once a pool of candidate ideas has been generated, organizations must evaluate them—assessing strengths, weaknesses, risks, and market fit, often through structured techniques such as SWOT or comparative

and scenario analysis, and incorporating customer perspectives. GenAI can support this stage by rapidly producing structured comparative analyses, simulating customer reactions or stakeholder perspectives, and flagging risks that a purely qualitative review might overlook. Conceptual work on AI-augmented new product development similarly positions transformer-based language models as tools that widen the problem and solution space explored by human teams rather than as substitutes for them (Bouschery et al., 2023). Evidence on the quality of AI-supported evaluation remains limited and conditional, however. In a study comparing GPT-4 with human experts, Kranzle and Sharratt (2025) find that LLM evaluations reach only moderate alignment with expert judgments, and only when the model is guided by a base evaluation framework and a spectrum-based few-shot prompt; the authors recommend using such frameworks primarily for large-scale idea screening and caution that privacy considerations arise when third-party models are used to assess proprietary ideas. Taken together, these findings point to a consistent recommendation: AI-supported evaluation should be followed, not replaced, by human judgment, particularly where evaluation criteria involve strategic fit, ethical considerations, or tacit organizational knowledge that is not well represented in the AI's training data. This pattern—AI-supported evaluation followed by human judgment—mirrors the sequencing already observed in ideation and reinforces the complementary rather than substitutive character of GenAI's contribution to innovation decision-making.

4.4. Product and Service Development

Beyond idea generation and evaluation, GenAI is increasingly used to support the more concrete work of developing product and service concepts—drafting feature lists, generating user stories, producing design alternatives, mapping customer journeys, and supporting rapid, low-cost experimentation with prototypes (experimentation is treated here as part of product and service development rather than as a separate stage). In engineering design contexts specifically, a recent survey of the literature identifies five domains in which large language models are being applied:

ideation and conceptual design, requirements engineering and problem definition, knowledge retrieval and documentation, computer-aided design and engineering automation, and systems engineering and decision support (Altun et al., 2026). Reported benefits in this literature include accelerated concept generation, reduced documentation burden, and more intuitive access to legacy technical knowledge, generated or modified directly from natural-language prompts. In service contexts, GenAI has similarly been used to integrate stakeholder input more directly into the early stages of service concept development, addressing a long-standing cause of new-service failure—namely, launching services without an adequately deep understanding of stakeholder needs (Noack et al., 2025). In collaborative new-product development settings, GenAI-based tools have been shown to expand the collective cognitive boundaries of development teams and to improve knowledge integration during early-stage work, although their contribution to deeper analytical reasoning, negotiation, and solution integration appears comparatively more limited, and teams that rely on such tools risk a degree of reduced collaborative naturalness and over-reliance on AI-generated suggestions (Zhang et al., 2026).

4.5. Business Model Innovation

GenAI's generative and synthetic capabilities extend beyond individual products and services to the business model level, informing value propositions, revenue models, customer segmentation, and channel strategy—often in conjunction with established frameworks such as the Business Model Canvas. A scoping review drawing on more than five hundred data points—spanning academic publications, company reports, and public commentary—proposes six propositions describing GenAI's impact on business model innovation and illustrates these with industry examples from software engineering, healthcare, and financial services (Kanbach et al., 2024). A complementary multiple-case study across eight firms of varying size and industry finds that GenAI's contribution to business model innovation is uneven across the three classic dimensions of value creation, value proposition, and value capture: firms find it

comparatively easier to innovate on value creation, more difficult on value proposition, and hardest of all on value capture, with genuinely architectural business model innovation—changes that reconfigure both internal and external structures—remaining a substantial challenge even for firms actively experimenting with GenAI (Ramaul et al., 2024). A further contribution in this stream cautions that, alongside its evident opportunities, GenAI's use in business model innovation is bounded by real technological limitations, and that firms must couple adoption with attention to new employee skills and security considerations if they are to capture GenAI's potential benefits without incurring undue financial, reputational, or legal risk (Stolyarov et al., 2024).

4.6. Commercialization

At the commercialization stage, GenAI supports the generation of marketing concepts, advertising copy, branding material, and broader content for customer communication, alongside customer segmentation and the design of communication strategies. Kshetri et al. (2024) conclude that using GenAI to create marketing content can raise the efficiency and productivity of marketing activities, and that GenAI-generated insights and content can improve the sales lead generation process, although they also discuss barriers to its use in marketing. In line with this evidence, and as with idea generation, the productivity gains available at this stage are considerable: GenAI can produce multiple campaign variants, tailored messaging for different segments, and draft creative assets far more rapidly than manual processes allow. The trust-related concerns discussed in Section 6 are especially salient here, since commercialization content is customer-facing and therefore carries reputational risk if AI-generated outputs are inaccurate, biased, or perceived as inauthentic (see also Stolyarov et al., 2024, on the financial, reputational, and legal risks of GenAI adoption).

4.7. Organizational Innovation

Finally, GenAI contributes to innovation not only in market-facing outputs but in the internal processes and structures of the organization itself—supporting workflow redesign, knowledge management, process innovation, decision support, and organizational learning. A case study of an LLM-based chatbot developed to support process modeling within a multinational manufacturing organization illustrates this application directly: developed in response to pain points identified by professional process modelers, the tool was found to meaningfully assist in the creation of process flow diagrams, offering a concrete example of how GenAI can be embedded into organizational innovation practice beyond the domain of product or service development (Ziche & Apruzzese, 2024). More broadly, GenAI's capacity to synthesize and structure organizational knowledge positions it as a potential enabler of organizational learning, provided that firms develop the complementary capabilities discussed in Section 6.5.

Table 2 summarizes the stage-specific roles of GenAI across the seven stages examined in this section, together with representative activities and illustrative outcomes.

Table 2. Applications of generative AI across innovation stages

Innovation Stage	GenAI Role	Representative Activities	Illustrative Outcomes
Opportunity recognition	Information synthesis	Summarizing market, customer, and competitor signals	Faster, broader environmental scanning
Idea generation	Idea partner	Brainstorming, analogical thinking, scenario generation	Higher idea volume and variance in quality
Idea evaluation	Decision-support partner	SWOT/scenario analysis, simulated customer feedback	Structured, AI-supported human evaluation
Product and service development	Design partner	User stories, prototypes, design alternatives, rapid experimentation	Faster concept iteration, reduced documentation effort
Business model innovation	Knowledge partner	Value proposition and revenue model variants	Easier value-creation innovation; harder value-capture innovation

Commercialization	Content generator	Marketing copy, branding, segmentation	Faster, more tailored go-to-market content
Organizational innovation	Process partner	Workflow redesign, knowledge management, process modeling	Improved knowledge integration and process documentation

5. Human–GenAI Co-Creation

5.1 Complementarity Between Human and AI Capabilities

The analysis in Section 4 consistently points to a pattern of complementarity rather than substitution. Human capabilities central to innovation include domain expertise, strategic judgment, contextual understanding, creativity, ethical judgment, and accountability—capacities that are difficult to encode fully into a statistical model and that carry legal and organizational responsibility that cannot be delegated to a machine. GenAI capabilities, by contrast, center on knowledge synthesis, rapid generation of alternatives, pattern recombination, scenario generation, rapid iteration, and large-scale information processing. Ali (2025), synthesizing findings from a systematic review of over one hundred peer-reviewed studies through an Antecedent–Mediator–Moderator–Outcome framework, similarly concludes that successful human–AI integration depends on aligning human judgment with algorithmic capability, built on mutual trust, transparency, and interpretability, with cognitive complementarity emerging as a key mediating mechanism linking collaboration to innovation outcomes. This complementarity is not incidental; it is the structural feature that makes co-creation, rather than automation, the appropriate frame for understanding GenAI's role in innovation. Table 3 summarizes these complementary capabilities.

Table 3. Human and GenAI capabilities in innovation

Dimension	Human Capabilities	GenAI Capabilities
Knowledge	Domain expertise, tacit and contextual knowledge	Knowledge synthesis and recombination across large corpora
Idea work	Creativity, problem framing, originality judgment	Rapid generation of alternatives, scenario variation
Evaluation	Strategic judgment, ethical judgment, ecological validity checks	Structured comparative analysis, pattern-based risk flagging
Process	Accountability, stakeholder management, validation	Rapid iteration, low-cost refinement of drafts
Outcome ownership	Decision authority, responsibility for outcomes	No independent accountability; outputs require human ratification

5.2. The Co-Creation Cycle

Building on this complementarity, GenAI-enabled innovation can be represented as a recurring cycle: human problem framing initiates the process; GenAI idea generation produces an initial set of alternatives; human evaluation assesses and selects among them; GenAI refinement develops the selected direction further; human validation confirms strategic and contextual fit; and experimentation tests the resulting concept against real-world conditions, feeding results back into the next iteration. These six steps describe the pattern of interaction between human and GenAI contributors; they are distinct from the seven innovation stages discussed in Section 4, and the experimentation step corresponds to the experimentation activities embedded in product and service development (Section 4.4). It is important to emphasize that this cycle should be understood as iterative rather than linear—a recurring exchange of human ↔ GenAI ↔ human ↔ GenAI—rather than a single hand-off from machine to human or vice versa. Empirical models of this cycle bear this out: the two-stage model proposed by Jiang and Wagner (2026) similarly frames co-creation as an AI-seeded ideation stage, in which the AI establishes a foundation of readily generated ideas, followed by a human-enhanced ideation stage, in which humans engage in less patterned, more exploratory refinement that both improves the initial ideas and introduces content that would not otherwise have been included, extending traditional accounts of process gains and losses in collaborative

creativity. Pedota et al. (2025) offer a complementary formal account, conceptualizing GenAI as a superposition of latent possibilities from which optimal creative outcomes arise when human agents actively select the most contextually appropriate entity, converging asymptotically toward better outcomes through repeated iteration—a formalization that gives analytical grounding to the intuitive picture of the co-creation cycle described above.

5.3. Human-in-the-Loop versus Human–AI Co-Creation

The distinction introduced in Section 2.3 between human-in-the-loop supervision and genuine co-creation deserves further elaboration here, because it carries direct implications for innovation management practice. In a human-in-the-loop configuration, the AI system performs a task largely autonomously, and the human's role is to supervise, review, and approve or reject the output at a defined checkpoint; the direction of influence is therefore largely one-way, from AI to human. In a co-creation configuration, by contrast, human and AI outputs continuously and reciprocally shape one another, such that the resulting artifact reflects an ongoing exchange rather than a single machine-generated draft subjected to a single human check. This distinction matters for innovation management because it affects where organizations should invest in training, how they should structure review processes, and how they should think about accountability: a human-in-the-loop process places the weight of accountability on the final approval step, whereas a co-creation process distributes engagement—and therefore also the opportunity to catch errors or introduce originality—across the entire interaction. Kadenhe et al. (2025) develop a related point in their review of human–AI co-design, arguing that mixed-initiative and explainable-AI approaches are important precisely because they allow designers to engage in this kind of iterative, trust-based exchange rather than a single-pass approval workflow.

5.4. AI as a Cognitive Partner

Drawing these threads together, GenAI can be understood as occupying several overlapping cognitive-partner roles within the innovation process: an idea partner, generating and varying candidate concepts; a knowledge partner, synthesizing and retrieving relevant information; a design partner, producing and iterating on visual or structural artifacts; and a decision-support partner, structuring comparative or scenario-based analysis to inform human choices. It is important, in describing these roles, to avoid framing GenAI as possessing human-like cognition, intention, or understanding. The value of these partner roles lies not in any claim about the AI's inner cognitive states but in the functional complementarity they provide: GenAI reliably performs certain generative and synthetic functions well, and organizations benefit from designing workflows that pair these functions deliberately with the judgment, contextual understanding, and accountability that only human contributors can supply. Hirst et al. (2025) provide direct empirical support for the importance of this pairing, showing that training workers in prompt engineering, combined with more human-like AI interface design, produces substantial improvements in co-creativity outcomes—particularly when the two interventions are combined—underscoring that the quality of human–GenAI co-creation is not fixed by the technology alone but is actively shaped by how organizations invest in worker skills and interface design.

6. Challenges and Boundary Conditions

6.1. Hallucination and Reliability

A first and widely documented boundary condition is the tendency of generative models to produce plausible-sounding but factually incorrect content, commonly referred to as hallucination. In innovation contexts, this creates a verification burden: outputs that inform market sizing, technical feasibility, or competitive positioning must be checked against reliable sources before being acted upon, since the fluency of GenAI-

generated text can create an unwarranted impression of accuracy. This concern is a central reason why the literature reviewed in Section 4 consistently frames GenAI's evaluative and analytical contributions as inputs to human judgment rather than as final determinations.

6.2. Bias and Idea Homogenization

A second boundary condition concerns algorithmic bias and the risk of idea homogenization. Because generative models learn statistical patterns from existing data, their outputs can reproduce and amplify biases present in that data, and similar prompts—especially when used repeatedly across an organization or industry—can produce similar outputs, potentially narrowing rather than expanding the diversity of ideas under consideration. This concern is reinforced by experimental evidence from a visual ideation task, in which participants who used an AI image generator during ideation exhibited higher fixation on the AI's initial example and subsequently produced fewer ideas, with less variety and lower originality, than a non-AI baseline (Wadinambiarachchi et al., 2024). This finding is a useful corrective to an overly optimistic reading of the ideation literature reviewed in Section 4.2: GenAI's capacity to expand the space of possible ideas is real, but it is not automatic, and depends heavily on how users approach prompt construction and how they respond to the AI's suggestions.

6.3. Intellectual Property and Ownership

A third boundary condition concerns intellectual property and ownership. Because generative models are trained on large corpora that may include copyrighted material, questions arise regarding the provenance of AI-generated content and the extent to which such content can be protected, licensed, or claimed as proprietary by the organization that generated it. Mariani and Dwivedi (2024) identify GenAI-enabled innovations and intellectual property as one of ten priority research themes at the intersection of GenAI and innovation management, underscoring that firms adopting GenAI in product development or commercialization contexts need clear internal policies governing the

ownership and permissible use of AI-generated content, particularly where such content contributes directly to patentable or brand-defining outputs.

6.4. Human Over-Reliance

A fourth boundary condition concerns the risk of human over-reliance on GenAI outputs, sometimes described as automation bias. Where organizational members come to trust AI-generated suggestions uncritically, the risk is not only that specific errors go unchallenged, but that critical thinking skills atrophy over time (deskilling) and that human agency in decision-making processes is gradually diminished. Zhang et al. (2026) document a related pattern in collaborative new-product development, observing that heavy reliance on GenAI-generated suggestions during collaborative work can reduce the naturalness of team collaboration itself, suggesting that over-reliance is not only an individual-level risk but can also degrade collective processes.

6.5. Organizational Capabilities

A fifth and more structural boundary condition concerns the organizational capabilities required to realize GenAI's potential contribution to innovation. These include AI literacy among employees, overall digital maturity, adequate data infrastructure, a receptive organizational culture, engaged leadership, and governance capabilities sufficient to manage the risks described above. Corvello (2025), applying a Technology Appropriation lens grounded in Adaptive Structuration Theory, argues that the impact of GenAI on innovation management is not determined by the technology alone but emerges through the ways in which organizations customize, reinterpret, and negotiate power dynamics around its use—implying that two organizations adopting the same GenAI tools may realize very different innovation outcomes depending on their organizational context and appropriation practices. Piller et al. (2024) add a complementary trust-based perspective, proposing that the appropriate level of trust placed in GenAI outputs should vary with task-specific needs and with the distinction between general-purpose and domain-expert models: inaccuracies in GenAI output may be tolerable, or

even creatively productive, during early-stage ideation, but tasks requiring domain-specific expertise demand higher accuracy and correspondingly higher organizational scrutiny. Table 4 summarizes these challenges, their descriptions, and the corresponding governance mechanisms.

Table 4. Challenges, risks, and governance mechanisms

Challenge	Description	Governance Mechanism
Hallucination and reliability	Fluent but factually incorrect outputs	Mandatory human verification of AI-generated claims
Bias and idea homogenization	Reproduced bias; convergent outputs from similar prompts	Prompt diversification; deliberate diversity checks on idea sets
Intellectual property and ownership	Unclear provenance and ownership of AI-generated content	Internal IP policies for AI-assisted outputs
Human over-reliance	Automation bias, deskilling, reduced critical thinking	Defined human checkpoints; training in critical evaluation
Organizational capabilities	Gaps in AI literacy, infrastructure, and governance	Investment in training, data infrastructure, and leadership sponsorship

7. Conceptual Framework

Synthesizing the preceding sections, this chapter proposes a Human–GenAI Innovation Co-Creation Framework, organized into four layers surrounded by a set of contextual conditions. The framework is presented in Figure 3.

Layer 1 – Human Capabilities comprises the distinctly human contributions to the innovation process: domain expertise, creativity, judgment, and strategic thinking. These capabilities are what allow raw, AI-generated alternatives to be interpreted, evaluated, and connected to organizational strategy and market context.

Layer 2 – GenAI Capabilities comprises the generative and synthetic contributions of the technology: generation, synthesis, recombination, simulation, and refinement. These capabilities expand the pool of alternatives available for human consideration and accelerate the iterative development of selected concepts.

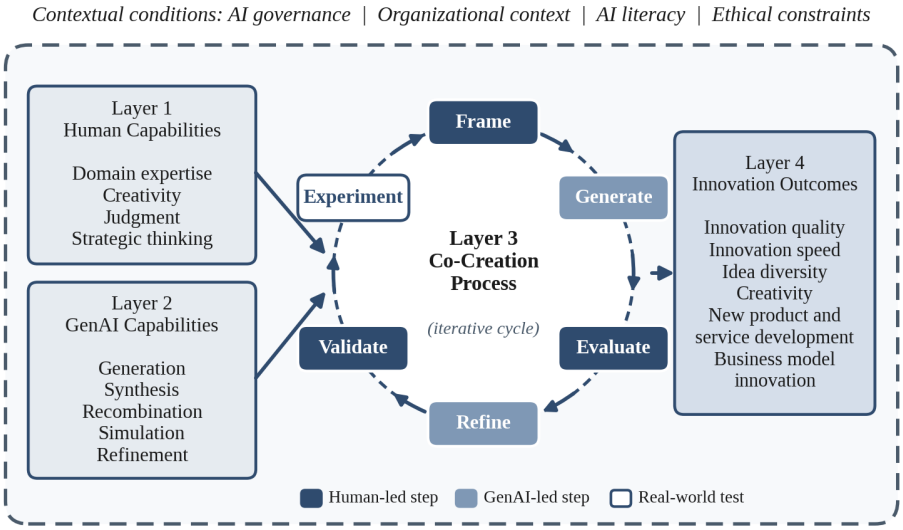


Figure 3. Human–GenAI innovation co-creation framework

Layer 3 – Co-Creation Process links these two capability layers through the recurring cycle described in Section 5.2: frame, generate, evaluate, refine, validate, and experiment. This layer is deliberately depicted as cyclical rather than linear, reflecting the finding, developed throughout Sections 4 and 5, that GenAI's contribution to innovation is most effective when embedded in iterative human–AI exchange rather than a single generative pass followed by a single human check.

Layer 4 – Innovation Outcomes comprises the downstream results that the co-creation process is intended to produce: innovation quality, innovation speed, idea diversity, creativity, new product and service development, and business model innovation. These outcomes correspond directly to the stage-specific contributions documented in Section 4.

Surrounding these four layers are the contextual factors identified in Section 6: AI governance, organizational context, AI literacy, and ethical constraints. These factors do not operate as a separate stage of the process but as conditions that shape how effectively the co-creation cycle in Layer 3 can translate the capabilities in Layers 1 and 2 into the outcomes in Layer 4. A firm with strong human capabilities and full access to capable GenAI tools, but weak AI governance or low AI literacy, would be expected—on

the logic of this framework—to realize a smaller share of the potential innovation outcomes than a comparable firm with stronger contextual conditions. This framework constitutes the principal conceptual contribution of the chapter and provides a structure against which future empirical research can be organized and tested.

8. Discussion and Implications

8.1. Theoretical Implications

This chapter's synthesis contributes to three adjacent literatures. First, it contributes to the human–AI co-creation literature by consolidating the distinction between human-in-the-loop supervision and genuine co-creation, and by integrating recent empirical models of co-creation (Jiang & Wagner, 2026; Pedota et al., 2025) into a stage-based account that connects directly to innovation management practice. Second, it contributes to the innovation management literature by explicitly reframing AI's role along a continuum from tool, to assistant, to collaborator, to co-creator—extending prior stage-based accounts of GenAI adoption in innovation (Mariani & Dwivedi, 2024) with a more granular account of the interactional dynamics involved. Third, it contributes to Generative AI research by consolidating evidence, drawn from ideation, evaluation, development, business model innovation, and commercialization contexts, that supports a complementarity-based rather than a substitution-based account of GenAI's organizational impact.

8.2. Managerial Implications

For practitioners, three implications follow directly from the analysis. First, organizations should deliberately design innovation processes around the complementary capabilities identified in Layer 1 and Layer 2 of the framework in Section 7, rather than either withholding GenAI adoption out of caution or delegating innovation decisions to GenAI outputs without adequate human evaluation. Second, human judgment should remain central to strategic and ethical decisions throughout the innovation process—particularly at the evaluation,

validation, and commercialization stages, where the reputational, legal, and strategic stakes of an error are highest. Third, AI literacy and governance capabilities should be built alongside GenAI adoption rather than treated as a subsequent concern: the boundary conditions reviewed in Section 6 indicate that firms which adopt GenAI tools without corresponding investment in employee training, data infrastructure, and governance mechanisms are likely to realize a narrower share of the innovation benefits documented in this chapter, and to bear a correspondingly larger share of the associated risks.

9. Conclusion

This chapter has argued that Generative AI is best understood not as a replacement for human innovators but as an active co-creator whose value emerges from its complementarity with human expertise, creativity, judgment, and contextual understanding. Three central messages summarize this argument. First, GenAI can contribute meaningfully across multiple stages of the innovation process, from opportunity recognition and idea generation through evaluation, development, business model innovation, commercialization, and organizational innovation, as documented throughout Section 4. Second, the greatest value from this technology is likely to emerge not from replacing human contributors but from deliberately combining human and AI capabilities within an iterative co-creation cycle, as set out in Sections 5 and 7—provided that organizations also attend to the reliability, bias, intellectual property, over-reliance, and governance challenges reviewed in Section 6. Third, and looking forward, innovation management can increasingly be conceptualized around a simple but consequential formula: Human + GenAI → Co-Created Innovation. Realizing this potential will depend less on the continued technical advancement of generative models themselves than on how deliberately organizations design the human–AI co-creation processes, capabilities, and governance structures through which that potential is put into practice.

Declarations

Ethics Committee Approval: This chapter does not fall within the scope of research requiring ethics committee approval, such as studies involving the collection of data from participants through surveys, interviews, focus groups, observations, experiments, or other qualitative and quantitative approaches; the experimental or scientific use of humans or animals (including materials/data); clinical studies conducted on humans; studies conducted on animals; or retrospective studies subject to personal data protection legislation. Therefore, ethics committee approval was not deemed necessary.

Use of Artificial Intelligence: In this chapter, ChatGPT was used for language editing and proofreading to improve the clarity and readability of the chapter. Claude was used to assist with model visualization, and Elicit was used to support the literature search and identification of relevant academic publications. The author reviewed the outputs generated by these tools and remains responsible for the final content of the chapter.

Conflict of Interest: The author declares that there is no conflict of interest.

Funding: The author declares that this chapter received no financial support from any institution, project, or funding body.

Third-Party Materials and Permissions: All figures and tables in this chapter were prepared by the author on the basis of the literature cited; no third-party figures, tables, images, or other materials requiring permission were reproduced.

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