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Generative artificial intelligence in innovation management: A preview of future research developments

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ABSTRACT

This study outlines the future research opportunities related to Generative Artificial Intelligence (GenAI) in innovation management. To this end, it combines a review of the academic literature with the results of a Delphi study involving leading innovation management scholars. Ten major research themes emerged that can guide future research developments at the intersection of GenAI and innovation management: 1) Gen AI and innovation types; 2) GenAI, dominant designs and technology evolution; 3) Scientific and artistic creativity and GenAI-enabled innovations; 4) GenAI-enabled innovations and intellectual property; 5) GenAI and new product development; 6) Multimodal/unimodal GenAI and innovation outcomes; 7) GenAI, agency and ecosystems; 8) Policymakers, lawmakers and anti-trust authorities in the regulation of GenAI-enabled innovation; 9) Misuse and unethical use of GenAI leading to biased innovation; and 10) Organizational design and boundaries for GenAI-enabled innovation. The paper concludes by discussing how these themes can inform theoretical development in innovation management studies.

1. Introduction

Advancements in digital technologies have engendered a transformation in human and business activities, forming the basis for the fourth industrial revolution (Schwab, 2017). Fueled by the growth of computational power and Big Data, computer engineers and scientists are designing and developing artificial intelligence (AI) systems and algorithms that are being increasingly adopted by individuals and organizations. Today, AI is arguably the most dominant technological paradigm and certainly a "pervasive economic and organizational phenomenon" (Von Krog, 2018: p. 404), whose associated opportunities and challenges are critically important for management researchers (Bamberger, 2018).

Currently, the technological and business communities are paying increasing attention to Generative Artificial Intelligence (GenAI): a form of AI that can drive innovation through new product discovery and development. Over the last three years, venture capital firms have invested more than 1.7 billion USD into GenAI solutions, with GenAI-enabled drug discovery and software coding getting the most funding (Wiles, 2023). The Research VP for Technology Innovation at Gartner, Brian Burke, stated that "…by 2025, we expect more than 30 % — up from zero today — of new drugs and materials to be systematically discovered using generative AI techniques" (Wiles, 2023).

In the media sector, an increasing number of companies (including Forbes, the New York Times, and the Washington Post) are deploying GenAI to produce entire articles from scratch that report on various topics, including politics, foreign affairs, financial markets, entertainment, sporting events, and crimes (Dörr, 2015; Longoni et al., 2022; Marconi, 2020). In the TV broadcasting sector, the South Korean TV broadcaster MBN has used GenAI to generate a deepfake of anchor-man Kim Joo-Ha (Foley, 2022) to report breaking news. In the movie industry, experts estimate that, by 2030, we will see a blockbuster movie created primarily from an AI translating text into video (Wiles, 2023). In the chemical industry, GenAI is able to independently design new chemical entities that retain the bioactivities of the given templates (Merk et al., 2018). In the pharmaceutical and healthcare industries, GenAI helps automate several parts of the drug discovery process, such as synthesis, molecular design, and synthesis planning (Grisoni et al., 2021). In fact, deep learning models can implicitly learn the desired molecular features, without the need for explicit, rule-based design

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constraints. More generally, GenAI is capable of designing and developing new molecules without any human intervention (except for a prompt). This can circumvent the traditional processes for pharmaceutical innovation (De Massis et al., 2018) and reduce the time (and costs) between discovery and going to market—as much as two thirds by some estimates. Marketing also stands to benefit from these developments (Chatterjee et al., 2021): Experts estimated that, by 2025, a third of advertising messages from large companies will be synthetically generated, up from less than 2 % in 2022.

With its wide deployment across industries and organizational functions, AI can not only trigger innovation, but “has the potential to change the innovation process itself, with consequences that may be equally profound” (Cockburn et al., 2018: p. 115). The growing importance of AI for innovation can be seen in a nascent research stream of innovation (management) studies covering AI (e.g., Verganti et al., 2020), as well as recent systematic literature reviews of that burgeoning research stream (e.g., Mariani et al., 2023). While this scholarly work has led to multiple definitions and typologies of AI in the management field (e.g., Davenport & Ronanki, 2018; Huang & Rust, 2018, 2021), we still do not recognize the full scale of opportunities that GenAI represents for innovation management research. As a consequence, we lack a comprehensive understanding of the major research themes that leading management scholars think might guide future research developments in innovation management research involving GenAI.

To bridge those knowledge gaps, this study combines a review of the academic literature with the results of a Delphi study—conducted on leading (innovation) management scholars who are familiar with GenAI. The goal was to identify and critically describe research themes that leading management scholars think will guide and shape future innovation management research revolving around GenAI. In doing so, the paper will allow innovation management researchers who are interested in GenAI to achieve more conceptual clarity, and from there, build a more consistent and connected body of knowledge on innovation (management) studies related to GenAI. Consequently, this study aims to answer the following research question:

RQ: What are the most relevant themes that will guide and shape future innovation management research revolving around GenAI?

To address this question, we combined and synthesized the academic literature with the results of a Delphi survey of leading innovation management scholars who are familiar with GenAI. In doing so, we move beyond the most recent systematic literature reviews on the topic (i.e., Haefner et al., 2021; Mariani et al., 2023) to generate new knowledge based on the critical thoughts of a panel of experts. Ten major research themes emerged that can guide future research developments at the intersection of GenAI and innovation management.

2. Literature review

2.1. Theoretical underpinnings, recent debate, and conceptualizations of AI in management

Management scholars disagree on who first began researching AI, but generally concur that AI began life in the literary domain—namely, the fictional book ‘*Runaround*’, published in 1942 by American author Isaac Asimov. Fifteen years later, the scientists John McCarthy and Marvin Minsky hosted the Dartmouth summer research project on AI at Dartmouth College, USA (Kaplan & Haenlein, 2019). From that point up until 2010, AI received relatively scarce attention from management scholars.

In the last decade, however, scholarly interest in AI has grown significantly (Emmert-Streib et al., 2020). Now, management scholars recognize that AI can generate relevant business outcomes (Davenport & Ronanki, 2018; Huang & Rust, 2018; Raisch & Krakowski, 2021; Von Krogh, 2018) and have therefore developed their own conceptualizations of AI for business. For instance, Davenport and Ronanki (2018) conceptualized and distinguished three types of artificial intelligence: (1) process automation; (2) cognitive insights; and (3) cognitive engagement. Process automation—sometimes referred to as robotic process automation (RPA)—is the cheapest and easiest AI to implement; as such, it typically generates a high (and quick) return on investment. The second type, cognitive insights, deploys algorithms and machine learning to detect patterns in vast volumes of data and interpret their meaning. Finally, cognitive engagement employs natural language processing chatbots, intelligent agents, and machine learning in order to connect people within and across organizations (e.g., employees, customers). Huang and Rust (2021) similarly conceptualized and distinguished three types of artificial intelligence: (1) mechanical; (2) thinking; and (3) feeling AI, which respectively handle routine, rule-based, and emotional tasks (Huang and Rust, 2021). Mechanical AI comes in the guise of robots, while thinking AI takes the form of conversational agents (Mariani et al., 2022). Relying on work by Nilsson (1971), Raisch and Krakowski (2021) defined AI as a concept that “refers to machines performing cognitive functions that are usually associated with human minds, such as learning, interacting, and problem solving” (p. 192). Drawing on Nilsson (2010), who defined AI as “that activity devoted to making machines intelligent” (p. 13), Cockburn et al. (2018) observed that AI covers three areas: robotics, symbolic systems, and learning systems. Only the latter ones represent a truly general-purpose technology that can be “a method to innovate”. Indeed, deep learning allows AI to “predict” physical and logical events with higher precision and accuracy compared to traditional statistical methods, which could be a boon for scientific, behavioral and technical research. Other scholars (e.g., Brynjolfsson & McAfee, 2014; Daugherty & Wilson, 2018; Davenport and Ronanki, 2018) have suggested that humans and machines must collaborate, rather than compete, in order to share their complementary strengths and achieve mutual learning (La Roche, 2017; Raisch & Krakowski, 2021). Overall, while several scholars maintain that there is no universally accepted definition of AI (Streinb et al., 2020), due to “intelligence” not being formally (and mathematically) defined, the management field has access to many working definitions of AI (see Huang & Rust, 2021; Nilsson, 2010).

Among *innovation management* studies, however, the conceptual history of AI is relatively more recent and features fewer definitions. For instance, relying on work by Nilsson (1971), Raisch and Krakowski (2021) defined AI as a concept that “refers to machines performing cognitive functions that are usually associated with human minds, such as learning, interacting, and problem solving” (p. 192). Similarly, Verganti et al. (2020) drew from insights derived from tech companies to argue that AI is a computer’s performance of simple tasks that were traditionally performed by human beings. Verganti et al. (2020) suggested that, as algorithms are increasingly employed for creative problem-solving, human design becomes an act of sensemaking, whereby humans decide which problems should or could be addressed. For instance, Netflix deployed data and AI algorithms to predict the content that it should create for users before understanding the market potential of the House of Cards series back in 2013. It also used AI algorithms to further develop the series afterwards. While the process was guided by AI, the company’s managers used their sensemaking to understand what customer problem should be addressed.

Drawing on Nilsson (2010), Cockburn et al. (2018) speculated that, among the three types of AI fields (robotics, symbolic systems, learning systems), learning systems constitute a novel general-purpose technology that also represents an “invention of a method of invention” (Cockburn et al., 2018: p. 116). Their analysis generated two key findings: first, from an innovation perspective, it is critical to distinguish between advances in the fields of robotics vs. deep learning as a general-purpose method of invention. Second, a few critical issues need to be resolved in order to exploit the potential of deep learning systems for innovation management and policy, including: 1) the evaluation of the new emerging science; and 2) the new barriers to entry induced by prediction methods across a wide spectrum of industries. As Dwivedi et al. (2021) observed in their multidisciplinary appraisal of AI, the "common thread amongst these definitions is the increasing capability of machines to perform specific roles and tasks currently performed by humans within the workplace and society in general" (Dwivedi et al., 2022: p. 2).

Two recent works have systematically reviewed AI in innovation management research (Haefner et al., 2021; Mariani et al., 2023). In their narrative review of the literature, which built on the behavioral theory of the firm, Haefner et al. (2021) did not specifically define AI. Instead, the authors argued that organizations increasingly rely on an expanding amount of information and knowledge that "is stored electronically and without human involvement" (ibidem: p. 2). As organizations become progressively digitized, innovation managers might not be able to effectively access and process such information. Accordingly, today's innovation managers may possess less information for innovation purposes—both qualitatively and quantitatively—than they had prior to the digital revolution. The authors therefore speculated that innovation managers will need to work side-by-side "with AI and machine learning algorithms in identifying and selecting opportunities as well as investigating what could be the organization's next competitive advantage" (Haefner et al., 2021: p. 3). In their own systematic literature review of AI and innovation, based on a drivers-phenomenon-outcomes framework, Mariani et al. (2023) borrowed Huang and Rust's (2022) definition of AI as "the use of computational machinery to emulate capabilities inherent in humans, such as doing physical or mechanical tasks, thinking, and feeling" (p. 31). Mariani and colleagues suggested that there are three types of drivers behind the adoption of AI for innovation (i.e., economic, technological, and social); accordingly, there are three types of outcomes (i.e., economic outcomes, competitive and organizational outcomes, and innovation outcomes). In their limitations section, Mariani et al. (2023) suggested that the management literature might need to integrate with the data science literature in order to enable the "emergence of innovation management research in the area of generative AI" (p. 20). Currently, their article is one of the few innovation management studies to explicitly mention *Generative AI*, albeit with no explicit definition nor conceptual description.

In summary, AI has been defined and conceptualized in several innovation management studies (e.g., Cockburn et al., 2018; Mariani et al., 2023; Raisch & Krakowski, 2021; Verganti et al., 2020), but *Generative AI* has not yet been explicitly analyzed in innovation management research. The sole exception is a passing mention by Mariani et al. (2023) in their systematic literature review.

2.2. Theoretical underpinnings, recent debate, and conceptualizations of GenAI in management

Generative AI (GenAI) is a broad term that captures AI systems "that can generate high-quality text, images, and other content based on the data they were trained on" (Martineau, 2023). More broadly, GenAI focuses on the generation of a wide range of outputs, such as text, code, images, pharmaceutical and biological elements (e.g., molecules), videos, music, and robotic actions. Thus, GenAI systems are different from "AI systems that perform other functions, such as classifying data (e.g., assigning labels to images), grouping data (e.g., identifying customer segments with similar purchasing behaviors), or choosing actions (e.g., steering an autonomous vehicle)" (Toner, 2023).

GenAI has a long history in the AI domain (Cao et al., 2023), dating back to the 1950s, when scholars were developing Gaussian Mixture models and Hidden Markov models. Those models were used to generate sequences of data in the guise of time series or speeches. Areas such as natural language processing (NLP) and computer vision (CV) relied on machine learning (ML) to advance algorithms for language and image generation. However, it was the emergence and advancement of deep learning (Peterson et al., 2022) that triggered enhanced performance for generative models. While these models – such as Generative Adversarial Networks (Goodfellow et al., 2014), Variational Autoencoders (Wu et al., 2021), and diffusion generative models (Croitoru et al., 2023) – had been developing over time, an intersection emerged in the transformer architecture. Introduced by Vaswani et al. (2017) with applications to NLP, the transformer architecture has become the dominant backbone of generative models. For instance, in the area of NLP, Bidirectional Encoder Representations from Transformers (BERT) and Generative Pre-trained Transformers (GPTs) (such as GPT-1 to GPT-4) deploy a transformer architecture. Vision Transformer and Swin Transformer utilize a transformer architecture in the area of CV, as does the text-to-image application DALL-E. Interestingly, the transformer architecture allows one to fuse different models and thereby enable multimodal tasks (i.e., simultaneously generating different types of content like images and music).

An increasing number of computer science scholars have explored different aspects of GenAI (e.g., Bengio et al., 2000; Brown et al., 2020; Deng & Lin, 2022; Devlin et al., 2018; Graves and Jaitly, 2014; Goodfellow et al., 2014, 2020; Mikolov et al., 2010; Macdonald, 1954; Radford et al., 2018; Schank & Abelson, 1975; Vaswani et al., 2017; Weizenbaum, 1966), but there are only a few recent articles on GenAI in the innovation management literature (e.g., Burger et al., 2023; Bouschery et al., 2023). For instance, Burger et al. (2023) illustrated the importance of AI for research methods by providing guidelines for utilizing AI (namely, ChatGPT) to develop a literature review. Bouschery et al. (2023) explored how transformer-based language models could be used by innovation teams in new product development.

3. Methods

Following the lead of Johnson et al. (2021), Skinner et al. (2015) and Suominen et al. (2023), we (1) conducted a literature review to identify the most relevant and cited articles at the intersection of GenAI and management and (2) conducted preliminary interviews with, and a Delphi study on, several of the identified authors. Developed within the Rand Corporation in the 1960 s, the Delphi methodology is a very well-known approach for engaging a group of experts on a given topic (Dalkey & Helmer, 1963).

3.1. Literature review deployed for the Delphi study

In line with the work of Johnson et al. (2021) and Suominen et al. (2019), we undertook a literature review to identify the Delphi study experts/participants and the items for the related questionnaire. In line with literature reviews conducted in other Delphi studies (e.g., Johnson et al., 2021; Suominen et al., 2019), we retrieved scientific articles indexed in the two reference scholarly databases: Clarivate Web of Science and Elsevier Scopus. Those databases index academic research across multiple disciplines (respectively representing more than 34,000 and 40,000 academic journals). Due to following rigorous and reliable selection criteria, these scholarly databases have the best coverage of academic research in the social sciences (Vieira & Gomes, 2009). We performed an advanced search in both databases on the 27th of June 2023, deploying the same set of terms and keywords across both WOS and Scopus. In both cases, we followed these steps: First, we adapted the research protocol and keywords used in a recent systematic literature review (Mariani et al., 2023) that dealt with artificial intelligence and innovation. The list of keywords used to cover GenAI included: "generative Artificial Intelligence" or "Generative Artificial Intelligence" or "GPT" or "GPT-1" or "GPT-2" or "GPT-3" or "GPT-4" or "ChatGPT" or "ClickUp" or "GrammarlyGO" or "Jasper" or "Copy.ai" or "Wordtune" or "Writesonic" or "Rytr" or "AlphaCode" or "GitHub Copilot" or "aiXcoder" or "TabNine" or "Figstack" or "Cody" or "SpellBox" or "AskCodi" or "BlackBox" or "Midjourney" or "DALL-E 2" or "NightCafe" or "BlueWillow" or "Bria" or "Stockimg" or "Fliki" or "Lumen5" or "Synthesia" or "DeepBrainAI" or "Runway" or "Pictory" or "Bard" or "Cohere Generate" or "Claude" or "StyleGAN" or "Bardeen" or "Rephrase.ai" or "Descript" or "Type Studio" or "GLIDE" or "Imagen" or "Bidirectional Encoder Representations from Transformers" or "BERT" or "RoBERTa" or "ERNIE" or "Bart" or "T5" or "Megatron" or "Murf.ai" or "Designs.ai" or "Soundraw" or "ChatFlash" or "ChatSonic" or "Scribe" or "VEED" or "Speechify" and several other GenAI proper names. While the collection of proper GenAI names is not necessarily comprehensive, it is broad enough to cover the most popular GenAI systems mentioned by leading IT consultancy companies like Gartner. Moreover, when proper names appeared with different spellings, we used the most widespread spellings (like in the case of "DALL-E 2", which is sometimes written as "DALL-E2"). The keywords deployed to cover innovation management were "innovat*" and "manag*".

In line with established methods for literature reviews (Snyder, 2019), and other systematic literature reviews (Mariani et al., 2023), we searched both the WOS and Scopus databases for combinations of the aforementioned keywords in all searchable fields, including the title, abstract, or keywords. We narrowed our search by only considering articles and review papers (Gaur & Kumar, 2018) in the English language that covered the subject areas of "Business" and "Management" for WOS and "Business, management and accounting" for Scopus. This yielded 255 documents for WOS and 709 documents for Scopus (the discrepancy stems from the subject classifications in the Scopus database being broader than in WOS: for instance, hospitality and tourism management journals do not get picked up using the classification "Business" or "Management" in WOS). Second, we merged the WOS and Scopus datasets and removed all duplicates (i.e., articles that were present in both databases were included only once in our final database), which produced a total of 712 documents. Three members of the research team carefully read each article's abstract to determine its relevance. All three agreed that 98 articles explicitly dealt with GenAI in management, whereas the rest just mentioned the word "innovat*" in a way that was loosely coupled with GenAI.

3.2. Delphi study

We saw the Delphi method as appropriate for our study since it can synthesize the critical reflections and thoughts of an expert panel, while also uncovering future research opportunities and challenges in the domain of interest. Unlike a common survey, which tries to identify what an already established phenomenon "is", the Delphi method attempts to address "what could be" when a phenomenon is emergent and/or new (Miller, 2006). To this end, we followed Skinner and colleagues' (2015) three-step guidelines for Delphi studies: 1) an exploratory stage; 2) a distillation stage; and 3) a utilization stage. In the first stage, we conducted open-ended interviews with 6 leading scholars: 4 management scholars who have published articles at the intersection of innovation and GenAI in academic journals rated as 3, 4, or 4* by the Chartered Association of Business Schools (CABS), and 2 leading computer scientists who have authored articles exploring how GenAI can support innovation activities and processes. The scholars were asked broad questions such as: "Do you think that the emergence and consolidation of GenAI will transform established concepts, frameworks, and constructs in innovation management research? If so, why and how? If not, why and how? What are the most relevant themes that will guide and shape future innovation management research revolving around GenAI?" The research team piloted the questions' effectiveness on one English-speaking research assistant with a knowledge of AI; the feedback helped to ensure that the wording was sufficiently simple and clear. Subsequently, we identified expert panelists using two criteria: The first was Delbecq et al.'s (1975) nominal group technique (NGT), a form of expert canvassing that involves creating a knowledge resource nomination worksheet (KRNW). The KRNW was informed by the literature review, through which we selected experts who had already published on the topic of GenAI in high-quality academic journals (rated 3 or more by the Chartered Association of Business Schools) in the area of management. The second was knowledge of experts in the area of interest, in line with Keil et al. (2002). In this way, we identified a total of 107 potential experts.

In the distillation stage, we combined the literature review and the open interviews to develop the arguments (i.e., the items) of the Delphi questionnaire. One researcher and two research assistants studying GenAI identified the Delphi arguments/statements and filled out an Excel spreadsheet table with them. Although 37 arguments were identified, the team selected only 25 arguments to simplify the work of the Delphi panelists. Two project team members independently scored the arguments in relation to the study's objectives. The 25 highest-scoring arguments were included in the Delphi questionnaire. Those two project members worked with 1 of the interviewed leading scholars (from the exploration stage) to ensure that the wording was unambiguous, the instructions were easy to follow, and the level of detail was appropriate (Gordon, 1994; Hallowell & Gambatese, 2010). The beginning of the questionnaire featured two working definitions in a short section named "Preliminary definitions": 1) Generative Artificial Intelligence (GenAI) is defined as AI systems "that can generate high-quality text, images, and other content based on the data they were trained on" (Martineau, 2023 – *IBM Research*); 2) Multimodal GenAI systems are defined as GenAI systems generating outputs from more than one type of data input, including text, voice, audio, video, pictures, etc. (Cao et al., 2023). In designing the materials, we addressed several potential forms of bias: (a) collective unconscious bias (Durkheim, 1982), by explicitly asking panelists to provide justification; (b) contrast effect and primacy effect (Bjarnason & Jonsson, 2005) bias, by randomizing the question order, and (c) dominance bias (Skinner et al., 2015), by ensuring expert anonymity. We sent the questionnaire to the 107 panelists via email and collected their results online. Following extant recommendations (Johnson et al., 2021; Skynner et al., 2015; Suominen et al., 2019), the study proceeded in two rounds. In the first round, the Delphi respondents were presented with arguments about GenAI and innovation management. The experts evaluated the significance of the arguments using 5-point Likert scales, as well as justified their position with open comments. In the first round, the experts were also free to answer open-ended questions about the opportunities and challenges that GenAI is likely to bring to innovation management research.

In round 2, in line with Suominen et al. (2019), we presented the panelists with the same arguments/items again, but with summaries of the first round's results. The summaries included descriptive values for the Likert-scale responses for each question, as well as a cohesive narrative assembled from the experts' comments, put forward by the project team. During round 2, the panelists were asked to re-evaluate the Likert scale variables, as well as comment on the provided narrative. The results from the Delphi study include the Likert-scale responses, as well as separate sections that represent the themes we derived from merging the experts' narratives. We want to emphasize that the argument narratives reflect the panelists' views, not that of the researchers.

The experts invited to the first round were sent an email invitation to participate in the Delphi process. Each expert was given a response time of two weeks, as well as two reminder messages. A total of 19 experts participated in the first round of the Delphi process. All 19 were invited back to participate in the second round and 11 ultimately returned. This number is more than acceptable based on leading methodological studies (e.g., Skinner et al., 2015) and management studies (e.g., Johnson et al., 2021) that deployed the Delphi method. For instance, Johnson et al. (2021) received only 5 responses in their second round, but argued that "Delphi studies are fundamentally different to, and should not be confused with, conventional statistical sampling and inferences techniques" (107).

In the third and final stage, utilization, we reported the results of the Delphi method to the second-round respondents. The first round's narratives formed the basis of the analysis, while the comments from the second round helped to improve said narratives. Besides deriving the qualitative narratives, we computed the average percent of majority opinions (APMO), which is typically used as a consensus measure in Delphi studies (Kapoor, 1987). Consensus—either as agreement or disagreement with the Delphi argument—can be defined as follows:

$$APMO = ((Agr + Disagr) / NumOp) \times 100 \quad (1)$$

where "Agr" is the majority agreement (including both "Strongly Agree" and "Somewhat agree"), "Disagr" is the majority disagreement (including both "Strongly disagree" and "Somewhat disagree"), and NumOp is the total number of opinions/responses. The APMO index is frequently deployed to indicate when an argument/item can be dropped from consecutive rounds of Delphi or when the Delphi exercise has reached a saturation point. In the present study, we report on the APMO score for both rounds, while the process description for the Delphi study is illustrated in Fig. 1. Following Johnson et al. (2021), we used the utilization stage to draft the findings (section 4) and develop the discussion section (section 5).

4. Findings

4.1. Findings from the literature review

Through the literature review, we identified 98 documents that explicitly dealt with GenAI in management. Among these articles, most tackled specific issues such as GenAI supporting management research (e.g., Burger et al., 2023) or enabling activities in the hospitality and tourism industries (Gursoy et al., 2023). For instance, Burger et al. (2023) discussed how AI can enhance research methods by generating guidelines for deploying ChatGPT to support the development of systematic literature reviews (SLRs), and the scientific research process more generally. They argued that using ChatGPT can make researchers' work faster without sacrificing reliability and replicability, but did not discuss critical elements for innovation management. Meanwhile, Gursoy and Song (2023) emphasized how ChatGPT might disrupt operations in the hospitality and tourism industry, namely by changing how customers search for information and make decisions, as well as how businesses produce, create, and deliver customized services and experiences. However, Gursoy and Song (2023) only mentioned innovativeness as a tourist-specific factor that can influence tourists' acceptance of ChatGPT. In a multi-author opinion piece edited by Dwivedi et al. (2023), most of the multidisciplinary contributions focus on disciplines other than innovation. The sole exception was the section written by Mariani, who suggested that "there is a long way before AI platforms such as ChatGPT could be capable to lead independently to meaningful product, process, or business model innovation. … As AI platforms and the underlying technology will evolve, future research will need to investigate if and to what extent the role played by generative AI will be increasingly relevant in triggering innovation outcomes" (Dwivedi et al., 2023: p. 6).

Upon careful inspection, we observed that only 2 of the 98 articles explicitly adopted an *innovation management disciplinary perspective* in relation to GenAI: namely, Bouschery et al. (2023) and Bilgram and Laarmann (2023). Bouschery and colleagues (2023) explored how transformer-based language models can be deployed to augment human innovation teams involved in the new product development (NPD) process. They put forward an AI-augmented double diamond framework to explain how such models can assist in NPD tasks, including idea generation, text summarization, and sentiment analysis. They also developed a research agenda to study the exploitation of language models in NPD and their role in hybrid innovation teams. By contrast, Bilgram and Laarmann (2023) focused on large language models (LLMs), using real-world examples to illustrate how they can augment the early stages of innovation, including exploration, ideation, and digital prototyping. The authors ultimately observed that GenAI could dramatically change the prototyping process, thereby compressing production time and costs.

To summarize, extant studies suggest that GenAI can create opportunities to support NPD, and more generally, innovation decisions and activities. That said, there is a paucity of management studies on how GenAI could potentially enrich innovation management research. For this reason, we used the literature review studies and the interviews to develop the 25 Delphi items (see Table A.1 in the Appendix).

4.2. Findings from the Delphi study

The 25 Delphi arguments can be seen in Table 1, which display the aggregate results for round 2. The APMO was 70.3 % for round 1 (details in Table A.2 in the Appendix) and 72.3 % for round 2 (see Table 1). The subsections below depict the experts' responses in narrative form. The text is based on the synopsis written by the researchers, which is derived from the open-ended comments by the Delphi experts within the Delphi rounds and, where relevant, also a few individual comments.

4.2.1. GenAI and innovation types

All of the experts argued that GenAI is likely to be a game-changer for innovation. The majority of them believed that AI would facilitate innovation without changing the basic types (e.g., product/process, radical/incremental, architectural/component, etc.). For instance, one expert said, "I think GenAI will greatly facilitate the process of innovation and help in outcomes that are incremental (for example, developing ideas that are based on customer feedback on existing products) as well as radical (for example, making potential connections between different ideas in different domains/fields). However, the broad types of innovation would remain the same." Another expert commented that "GenAI continues the technological development experts have seen for the past few years. As such, I think the types of innovation that we know won't change much, if at all." Another expert agreed that the adoption of GenAI would not change innovation taxonomies, but would deeply affect innovation for products and especially business models. Interestingly, one scholar expressed a different and interesting opinion: "Perhaps not in the short term, but in the long term GenAI will challenge traditional notions of artistic innovation and GenAI generated artistic content (such as music) might emerge as an entirely new creative domain." Most scholars agreed that GenAI can enable the fusion and hybridization of different types of innovation – such as product, process and marketing innovation – thus paving the way for the emergence of entirely new business models.

4.2.2. GenAI, dominant designs and technology evolution

The vast majority of experts mentioned that the GenAI S-curve (S-curves are often used in innovation management to describe the diffusion of a technology; they basically express the cumulative number of technology adopters across time) is showcasing an unusually fast adoption stage following introduction. Two scholars argued that conversational GenAI systems such as ChatGPT are likely to become the fastest-adopted technology by consumers (and likely also by businesses) after the smartphone and the Internet. One expert recalled a Reuters news article about how ChatGPT became "the fastest-growing consumer application in history" after reaching 100 million active monthly users just two months after launch (Hu, 2023). Another panelist mentioned that business commentators have suggested that ChatGPT is already the fastest-growing technology in history (Bove, 2023). While many scholars agree that the shape of a technology S-curve is not set in stone, and therefore limits the prescriptive utility of the S-Curve model, the two experts mentioned above independently emphasized that GenAI offers many unprecedented advantages across many industries and can seamlessly fit with customers' and businesses' current abilities. That said, all the panelists felt that, despite its fast diffusion and adoption, GenAI is in the early stages of its technological lifecycle. In particular, one mentioned that "I don't think a dominant design has emerged yet. I presume we are still in the era of ferment – whereby experimentation of different models/technologies are being tried out (in different domains) … […] We are not yet sure of how the GenAI technologies can be used in the different domains. I think a dominant design will emerge once valuable use cases are identified and validated, that in turn lead to network effects among adopters."

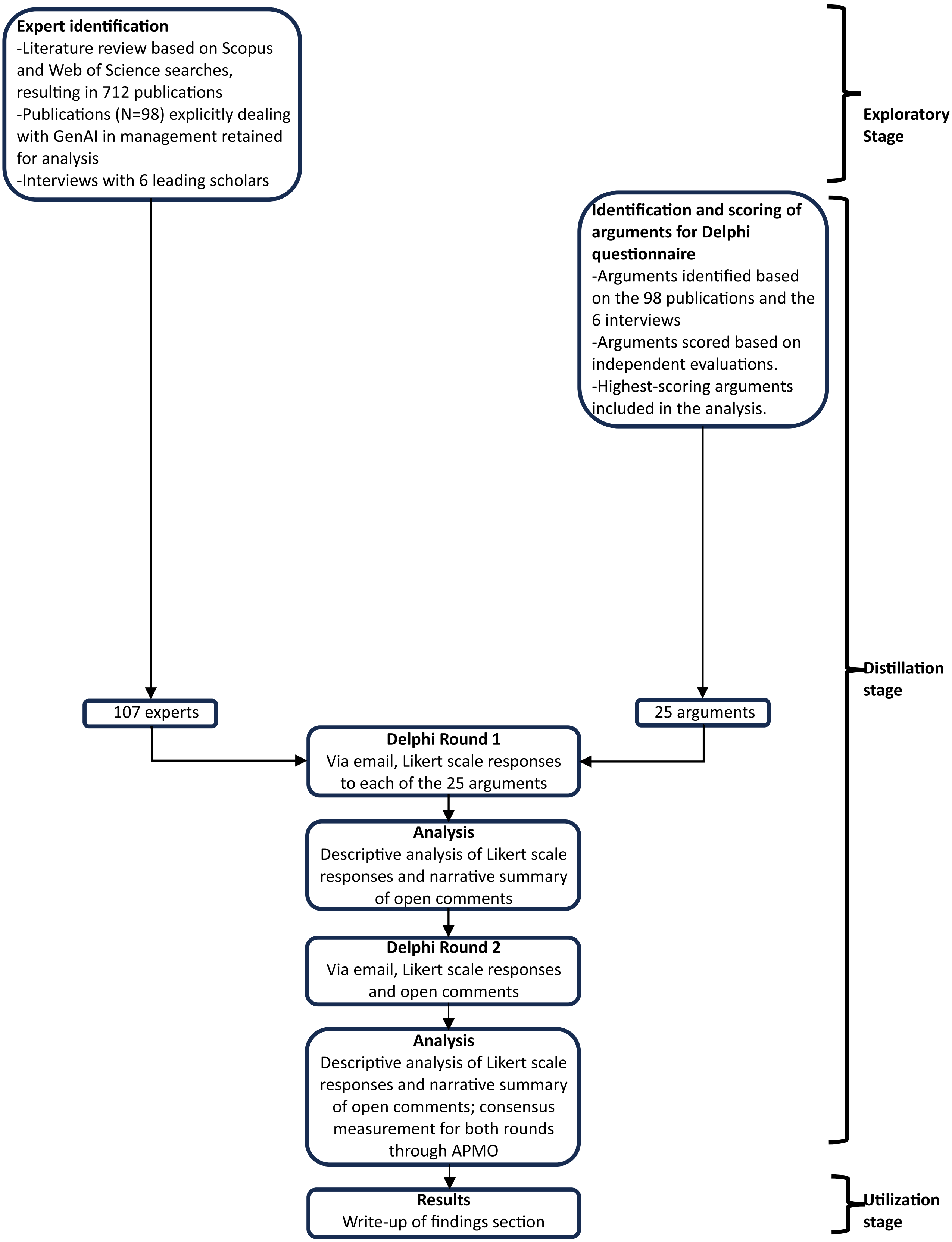

Fig. 1. Process description for the Delphi study.

Table 1
Aggregated results from Round 2 (common sized values).

#	Theme	Delphi argument	Strongly disagree	Somewhat disagree	Neither agree or disagree	Somewhat agree	Strongly agree	Unable to comment	Number of Opinions
1	1	GenAI will not lead to the conceptualization of innovation types that go beyond extant innovation taxonomies (e.g., product/process, radical/incremental, architectural/component, etc.)	0.0 %	0.0 %	9.1 %	45.5 %	45.5 %	0.0 %	100.0 %
2	1	Business model innovation might be significantly modified by the presence of GenAI	0.0 %	0.0 %	11.1 %	33.3 %	55.6 %	0.0 %	100.0 %
3	2	A dominant design among GenAI systems has not emerged yet	10.0 %	0.0 %	0.0 %	80.0 %	10.0 %	0.0 %	100.0 %
4	2	The evolution of GenAI systems can be captured through extant technology evolution frameworks	0.0 %	0.0 %	0.0 %	22.2 %	66.7 %	11.1 %	100.0 %
5	3	GenAI-enabled scientific creativity will be conceptualized differently than traditional scientific creativity	0.0 %	9.1 %	9.1 %	63.6 %	18.2 %	0.0 %	100.0 %
6	3	GenAI-enabled artistic creativity will be conceptualized differently than traditional artistic creativity	0.0 %	0.0 %	0.0 %	81.8 %	18.2 %	0.0 %	100.0 %
7	4	GenAI will lead to to the conceptualization of novel forms/types of intellectual property (protection) in innovation management	0.0 %	10.0 %	10.0 %	50.0 %	30.0 %	0.0 %	100.0 %
8	4	GenAI will undermine the way we currently conceptualize intellectual property in innovation management	9.1 %	9.1 %	9.1 %	36.4 %	36.4 %	0.0 %	100.0 %
9	5	GenAI will modify the way we currently conceptualize deliberate vs. emergent strategies in New Product Development	18.2 %	63.6 %	9.1 %	9.1 %	0.0 %	0.0 %	100.0 %
10	5	GenAI will change how management scholars construe and conceptualize the New Product Development process	9.1 %	27.3 %	18.2 %	18.2 %	18.2 %	9.1 %	100.0 %
11	5	GenAI will change how management scholars construe New Product Development teams	0.0 %	9.1 %	18.2 %	36.4 %	27.3 %	9.1 %	100.0 %
12	5	GenAI will change how management scholars construe and conceptualize experimentation and validation	0.0 %	11.1 %	11.1 %	33.3 %	44.4 %	0.0 %	100.0 %
13	5	GenAI will change how management scholars construe and conceptualize new product testing	0.0 %	0.0 %	20.0 %	40.0 %	40.0 %	0.0 %	100.0 %
14	6	Multimodal GenAI is likely to have a more positive influence on the adopting firm’s competitive advantage than unimodal GenAI systems	0.0 %	9.1 %	9.1 %	45.5 %	27.3 %	9.1 %	100.0 %
15	6	Multimodal GenAI is likely to have a more positive influence on the adopting firm’s innovation performance than unimodal GenAI systems	0.0 %	10.0 %	20.0 %	40.0 %	20.0 %	10.0 %	100.0 %
16	7	GenAI will make innovation management research on platform ecosystems more relevant than before	0.0 %	11.1 %	11.1 %	33.3 %	44.4 %	0.0 %	100.0 %
17	7	GenAI-enabled innovation is more likely to be an open, rather than closed, form of innovation	9.1 %	27.3 %	18.2 %	18.2 %	18.2 %	9.1 %	100.0 %
18	7	GenAI will change how innovation management scholars make sense of agency of innovation activities and processes	0.0 %	9.1 %	18.2 %	36.4 %	36.4 %	0.0 %	100.0 %
19	7	Human-GenAI interactions will change innovation activities and processes	0.0 %	0.0 %	10.0 %	40.0 %	50.0 %	0.0 %	100.0 %
20	8	Policymakers and lawmakers will need novel frameworks to regulate GenAI-enabled innovation	0.0 %	0.0 %	0.0 %	44.4 %	44.4 %	11.1 %	100.0 %
21	8	Anti-trust authorities should be equipped with new frameworks to enforce regulations related to GenAI-enabled innovation	0.0 %	9.1 %	27.3 %	36.4 %	18.2 %	9.1 %	100.0 %
22	9	The misuse of GenAI can generate biased innovation outcomes	0.0 %	22.2 %	11.1 %	44.4 %	11.1 %	11.1 %	100.0 %
23	9	The unethiical use of GenAI can generate innovation outcomes that benefit only a subset of stakeholders	0.0 %	9.1 %	9.1 %	45.5 %	27.3 %	9.1 %	100.0 %
24	10	GenAI is likely to modify organizational boundaries	0.0 %	0.0 %	10.0 %	40.0 %	50.0 %	0.0 %	100.0 %
25	10	GenAI is likely to modify organizational design and coordination	0.0 %	0.0 %	10.0 %	40.0 %	50.0 %	0.0 %	100.0 %

4.2.3. *Scientific and artistic creativity and GenAI-enabled innovations*

Most experts argued that scientific and artistic creativity will be enhanced and empowered through GenAI—and may even be conceptualized differently to accommodate this technology. Several of them felt that traditional concepts of individual and organizational human creativity will be replaced by brainstorming between humans and GenAI systems. The experts suggested that this will be more relevant for artistic creativity where physical laws (the kind that constrain the harder sciences) do not impede idea generation or implementation. One of them went on to mention that “it is not surprising that so many creative design and music software are increasingly integrating GenAI.”

4.2.4. *GenAI-enabled innovations and intellectual property*

The majority of the experts stated that the advancement of GenAI will render extant intellectual property protections obsolete. One of them argued that “it is likely that in a couple of decades from now, governments in some countries – those more inclined to encourage technological innovation like here in the US – will start developing laws that significantly modify copyright.” Those same experts suggested that GenAI will lead to new conceptualizations of intellectual property (protection) in innovation management. Several agreed that governments need updated frameworks that allow GenAI systems to work at full capacity; the most radical expert even argued that current copyright law “should go away” in order to fulfil that goal. That said, a significant minority of experts suggested that intellectual property is here to stay and largely in its current form (i.e., as patents, trademarks and copyrights). This latter group of experts mentioned that GenAI providers should instead coordinate continuously with patent offices and copyright law enforcement bodies.

4.2.5. *GenAI and new product development*

Most of the experts disagreed that the presence of GenAI would make the difference between deliberate vs. emergent strategies in New Product Development (NPD) more pronounced. Several of them argued that emergent strategies are often a matter of serendipity for employees and managers, although it is possible for GenAI to produce unexpected solutions via embedded elements of "positive" randomness. That "positive" randomness could help amplify humans' capacity to develop unconventional ideas during the NPD process. Furthermore, the majority of experts argued that GenAI will change how management scholars construe NPD teams. Indeed, the dynamics within NPD teams will need to change to accommodate the increasing inclusion of machines,. As a corollary of these first two points ("positive" randomness injected by GenAI systems and more diverse innovation teams), most of the experts expected that innovation management scholars would modify the way they construe and conceptualize the NPD process. Indeed, the collaborations between humans and GenAI systems will impact the structure, duration, and efficiency of workflows. Additionally, most experts felt that GenAI would enable more real-time experimentation and validation techniques, empowering innovation managers to quickly pivot their ideas into products/processes/business models. Likewise, GenAI would improve new product testing by allowing for real-time uptake and processing of consumer preferences and needs. For instance, one expert mentioned digital prototyping as a way to quickly and cheaply test new products.

4.2.6. *Multimodal/unimodal GenAI and innovation outcomes*

The majority of experts argued that multimodal GenAI systems (i.e., GenAI systems that generate outputs from more than one type of data input, including text, voice, audio, video, and pictures) are likely to play a bigger role in firms' competitive advantage and innovation performance compared to unimodal Generative AI systems. Several of the panelists mentioned that multimodal GenAI systems can enhance users' experience, and therefore their satisfaction, by making the content richer, more interactive, and highly personalized. As one expert pointed out, personalized content can be particularly relevant in digital marketing and communication campaigns, which can leverage browsing history, textual queries, visual preferences and numeric data (concerning content size and prices). Third, the experts stressed that multimodal GenAI can generate (new) content that is contextually relevant. Finally, multiple data modalities allow GenAI systems to ingest data from disparate sources, thereby creating many (potentially countless) sources of innovation. Overall, multimodal GenAI systems have broader implications for user experience and satisfaction than their unimodal counterparts.

4.2.7. *GenAI, agency and ecosystems*

Most of the panelists maintained that the introduction and consolidation of GenAI systems are likely to create a dense network of actors and stakeholders – not all of them human – who will increasingly interact in pursuit of innovative outcomes. This implies that GenAI-enabled innovation will happen through distributed agency, which will also entail human-GenAI interactions that will modify innovation activities and processes. For those reasons, most of the experts believed that GenAI will heighten the relevance of (digital) platform ecosystems research.

4.2.8. *Policymakers, lawmakers and anti-trust authorities in the regulation of GenAI-enabled innovation*

Most experts argued that extant framework for regulating entities that pursue GenAI-enabled innovation should be updated, if not radically modified. This implies a need for new policies, laws, and regulations. Likewise, anti-trust authorities may need to revise their toolkits in order to ensure that market competition is not distorted by certain companies using (or abusing) GenAI systems to build dominant positions.

4.2.9. *Misuse and unethical use of GenAI leading to biased innovation*

The vast majority of the panelists agreed that the unethical application of GenAI can bias innovation. Several mentioned deepfakes as an innovation with several detrimental consequences, including reputational damages to individuals and organizations, job losses, distortions in market competition, and the spread of misinformation. However, most countries currently lack a regulatory framework that can offer protection against content generated through the misuse of GenAI. Secondly, the experts noted that GenAI systems are increasingly generating misinformation (e.g., fake posts or reviews) that can bias—if not paralyze—consumers' and managers' decision-making. This can eventually lead to suboptimal decisions and substantive losses. Lastly, the experts agreed that GenAI models can be biased against certain individuals or groups, based on not only the model's training data, but also the absence of ethical controls on GenAI algorithms. This means that certain groups of stakeholders might disproportionately benefit from GenAI-enabled innovation compared to others. In short, GenAI systems need to comply with ethical standards in order to ensure that innovation outcomes are ethical and fair themselves.

4.2.10. *Organizational design and boundaries for GenAI-enabled innovation*

Most of the Delphi participants mentioned that GenAI will radically redefine the notions of knowledge and expertise. For instance, engineers who are proficient in prompting might play a critical role in deploying GenAI systems, which could lead to the creation of not only new jobs, but even new organizational units. For instance, R&D labs may gain control over work design. Following this line of reasoning, some panelists stated that the redefinition of expertise and knowledge will likely require a modified allocation of power within and across organizations. In this vein, several mentioned that organizational boundaries will need to be more porous, since most innovators within the organization will not need deep technical knowledge of the subject matter. Several experts mentioned that within or outside the organization, trainers will support innovation workers and managers in interacting with GenAI systems. Finally, several experts mentioned that GenAI may affect coordination, insofar as a large number of tasks may have to be atomized into smaller modular subtasks that can be outsourced.

5. Discussion

This study combined a review of the academic literature with the results of a Delphi study—conducted with leading (innovation) management scholars who are familiar with GenAI—to identify and critically describe the most relevant future research themes for this domain. We identified 10 key research themes that are described in section 4.2. In the remaining part of this section, we critically discuss the themes in relation to extant innovation management research to inform theoretical development in innovation management studies.

5.1. *GenAI and innovation types*

According to the innovation management experts we interviewed, GenAI will not modify extant innovation taxonomies (e.g., product/process, radical/incremental, competence-destroying/competence-enhancing, architectural/component, open/closed innovation, etc.) in the short-term. The innovation management literature suggests that there are four measurable forms of innovation: product, process, organizational, and marketing innovation (Gault, 2018). The first two forms (product and process) are typically captured through standard innovation questionnaires. So far, GenAI has mainly been associated with product innovation: namely, the new content that it can generate for end-users (consumers and managers). However, by synthesizing this innovation typology (Gault, 2018) with the outcomes of our Dephi study, we can realistically imagine GenAI enabling multiple forms of innovation (see Table 2):

As far as the radical vs. incremental innovation taxonomy, Dewar and Dutton (1986) noted that "radical innovations are fundamental changes that represent revolutionary changes in technology. They

Table 2
A typology of GenAI-enabled innovation.

Type of Innovation (Gault, 2018)	Types of GenAI-enabled innovation	Business examples and use cases
Product innovation	***GenAI-enabled Product Innovation (GenAIProdI)***GenAI used to generate a new product or improve an existing product	***Use cases***: new texts, paintings, music, pictures, movies, molecules. ***Real examples***: ChatGPT for text generation; Dall-E 2 for images generation; Stability AI for music generation. **Quote/s:**In November 2022, the Canadian musician Grimes made a bold prediction. "I feel like we're in the end of art, human art," she said on Sean Carroll's *Mindscape* podcast. "Once there's actually AGI (Artificial General Intelligence), they're gonna be so much better at making art than us." Today this seems like the reality with GenAI systems such as Riffusion.
Process innovation	***GenAI-enabled Process Innovation (GenAIProcI)***GenAI used to generate a new process or improve an existing process	***Use cases***: new algorithms for discovery of new drugs/materials (with reduced costs and lead times); new algorithms to translate text into images (and vice versa); synthetic data for keeping (medical) data anonymous; new algorithms that modify the process of creating new software. ***Real examples***: Biotech companies such as Generate Biomedicines, Iktos, and Terray Therapeutics leverage GenAI for de novo drug design; Roche using synthetic medical data for clinical research; Freshworks using ChatGPT to reduces coders' time to create a complex software application from 10 weeks to 1 week. **Quote/s:** Ely Berlin of Terray Therapeutics: "There are thousands of problems sitting out there that we don't know the answer for… So having a platform that lets us go faster, be precise and scale can really transform the opportunities in front of us" (Vedantam, 2022).
Marketing innovation	***GenAI-enabled Marketing Innovation (GenAIMarI)***GenAI used to improve marketing activities	***Use cases***: deepfakes and automated communication messages used for product advertising; automated communication used to create personalized customer experiences and improve customer relationship management. ***Real examples***: Zalando used deepfake technology. Based on a single video shoot, it created 60,000 video messages for every town and village in Europe. Subsequently, using Facebook's ad targeting, they showed users the specific video which mentioned their hometown. BCG used predictive analytics and machine learning to create a real-time personalization experience for Starbucks, which led to a 150 % increase in user interaction. Netflix's recommendation system deploys analytics about viewers' behaviors and hobbies to recommend movies and series. Conversational company Haptik develops sales chatbots for companies to improve their conversational commerce. The Dalí Museum in St. Petersburg (USA) deploys a deepfake of the artist Salvador Dalí to greet guests and generate a more engaging experience for visitors. Coca Cola is using ChatGPT and Dall-E to craft personalized ad copy, images, and messaging. UK-based energy supplier Octopus Energy has built ChatGPT into its customer service channels to handle 44 percent of customer inquiries. **Quote/s:** "I believe deeply — to my bones — that the most important development in the history of marketing is machine learning…it will fundamentally change our relationship with consumers." — Kristin Lemkau, JPMorgan Chase CMO
Organizational innovation	***GenAI-enabled Organizational Innovation (GenAIOrgI)***GenAI used to improve organizational features	***Use cases***: Algorithms supporting HR recruiting activities; algorithms supporting the design and redesign of organizations undertaking digital transformation; algorithms used to enhance communication with colleagues. ***Real examples***: The Paradox AI algorithm "Olivia" helps in screening candidates and even answering their questions during the HR recruitment process. The Dutch beverage conglomerate Heineken began its agile transformation in the IT department, where leadership worked hand-in-hand with other departments, outside suppliers, and the company's employee work council. The collaborative workspace platform Slack has created an app allowing its users to leverage ChatGPT to help with managing workflows, boosting productivity and communicating with colleagues. HireVue is the most popular AI-powered recruitment platform, deployed in over 700 large companies such as Unilever, Vodafone, PwC, and Oracle. The platform is effective in reducing hiring times by 90 % and increasing hiring diversity by 16 %. **Quote/s:**IBM has developed its own chatbot for recruitment purposes. Their managers comment that "it is one of the busiest chatbots at IBM, answering 700 questions a day. New hire chatbots are particularly helpful because they resolve the challenge of not knowing who to ask for help. IBM's goal with chatbots is to get answers to employees quickly and accurately while reducing the amount of effort it takes to support HR programs. The time saved can then be spent on experts answering more complex questions and problems about HR issues".

represent clear departures from existing practice (Duchesneau et al., 1979; Ettlie, 1983). In contrast, incremental innovations are minor improvements or simple adjustments in current technology (Munson and Pelz 1979). The major difference captured by the labels radical and incremental is the degree of novel technological process content embodied in the innovation and hence, the degree of new knowledge embedded in the innovation" (pp. 1422–1423). Most Delphi participants agreed that GenAI will support both incremental and radical innovation (see Table 3):

Table 3
A Taxonomy of GenAI-enabled Radical vs. Incremental Innovation.

Type of Innovation (Dewar & Dutton, 1986)	Types of GenAI-enabled innovation	Business examples and use cases
Radical innovation	***GenAI-enabled Radical Innovation (GenAIRadI)*** GenAI used to support radical innovation	***Use cases***: creation of entirely new forms of content that may usher into new artistic domains (such as GenAI-generated art, music, and literature) as well as new scientific domains such as generative chemistry. ***Real examples***: Microsoft has recently launched the project "Generative chemistry", aimed at training machine learning systems to help chemists and pharmacists to more quickly find relevant candidates for their new drug projects. **Quote/s:**"The process for developing new drugs is incredibly complex, requiring the evaluation of hundreds of thousands of candidate compounds before a project reaches the clinical trial stage. This process is slow, costly, and requires immense amounts of expert time […] We train machine learning systems to help chemists and pharmacists to more quickly find new relevant candidates for their projects" (Microsoft, 2023).
Incremental innovation	***GenAI-enabled Incremental Innovation (GenAIIncI)*** GenAI used to support incremental innovation	***Use cases***: new music, molecules, pictures, movies. ***Real examples***: Midjourney for image generation; Riffusion for music generation; OpenAI GPT-4 for text generation. **Quote/s:** "ChatGPT can quickly automate the production of pers-uasive emails, engaging advertisements, or captivating social media posts, effectively scaling up the marketing output" (Jamie Chen and Kaushik Jayaram, 1023; Simon Kucher). "AI will greatly facilitate incremental innovation andhelp in outcomes that are incremental (for example, developing ideas that are based on customer feedbackon existing products) ."

5.2. GenAI, dominant designs and technology evolution

The consensus among our interviewed experts was that GenAI is still in the "era of ferment". Here, we blend their observations with extant innovation management theory. In the literature, Utterback and Abernathy (1975) conceived of—and empirically validated—a major technology evolution framework whereby a technology passes through different phases. In the first phase, named the *fluid phase*, there is considerable uncertainty about both the technology and its market. Products and services based on the technology might suit the needs of market niches, but are nonetheless expensive, crude, or unreliable. In this phase, firms experiment with different form factors or product features to assess the market response. Eventually, producers and customers begin to reach some consensus about the desired product attributes and a dominant design emerges. Utterback and Abernathy (1975) named this the *specific phase* because the innovations—whether in products, materials, or manufacturing processes—are all specific to the dominant design. The dominant design establishes a stable architecture for the technology and enables firms to focus their efforts on process innovations (that make the design more effective and efficient) or incremental innovations (to improve components within an architecture). For instance, in most of the international meetings and events involving political leaders from different countries, professional human translators are still in use. On the other hand, AI-empowered services such as Interprefy are increasingly being used by corporations (even leading tech developers such as Alphabet/Google, Facebook, Intel) throughout the globe.

Building on Utterback and Abernathy's (1975) proposed model, Anderson and Tushman (1990) studied the history of several US industries (cement, glass, and computers) and found that each tech discontinuity prompted a period of turbulence and uncertainty, which they termed the *era of ferment*. The new technology could offer breakthrough capabilities, but there might be little agreement about what the major subsystems of the technology should be or how they should be configured. As the new technology replaces its predecessor, firms engage in a design competition where they experiment with different technological forms. Anderson and Tushman (1990) found that the dominant design never takes the form of the original discontinuity, nor that of the technology's leading edge. Instead, the dominant design tends to bundle a combination of features that best fulfill the demands of the majority of the market. Developments in GenAI are likely to generate a shift from highly skilled technical labor to capital-intensive research production with fixed-cost investments in GenAI (Cockburn et al., 2018). Currently, there are no organized marketplaces for GenAI research tools and the standards for these tools are in a nascent stage (Ferràs-Hernández et al., 2023; Morley et al., 2020; Nagendran et al., 2020). In the last few months, we have observed tech companies try to shape a new market for GenAI (research) tools: see the initiatives and projects launched by OpenAI and Microsoft (e.g., ChatGPT), or by Google/Alphabet (e.g., Apprentice Bard).

Almost all of the experts noted that GenAI is in its era of ferment, since no dominant design has emerged yet. This means that the major players will continue competing for some time. The experts also agreed that the dominant design will not necessarily be the best-performing GenAI system, but the most adopted one. Three experts added that it is likely that there will be as many dominant designs as there are applications/business fields. Most of the experts cited several companies as likely candidates for achieving a dominant design: OpenAI, Microsoft, Google/Alphabet, Facebook, Salesforce, and Amazon (see Fig. 2). Someone even mentioned Baidu and Tencent. One even argued that each of the aforementioned companies could develop a dominant design for its own platform, similar to what Intel achieved for computer processors (with the "Intel Inside" branding).

Most experts pointed to the fact that key hardware suppliers like Nvidia, IBM, AMD and Intel will hold relevant bargaining power. Two experts ventured further to suggest that a dominant design will be one that is extremely simple for adopters to deploy. One said that a dominant architecture will likely be based on transformer models (Vaswani et al., 2017), which are very effective in natural language generation (e.g., ChatGPT, GPT-4). This represents an architectural innovation that can

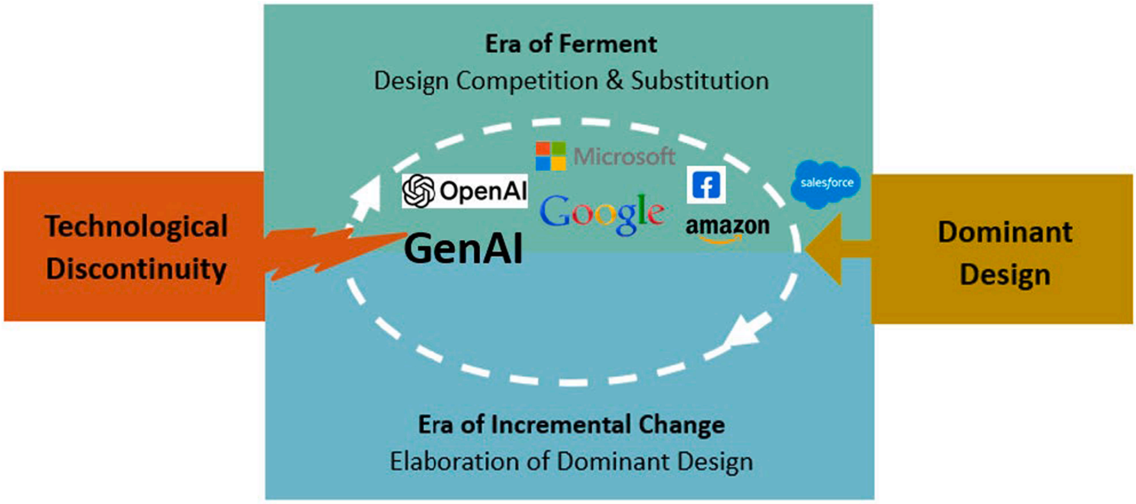

Fig. 2. GenAI technology cycle. Source: own work adapted on the basis of Anderson & Tushman (1990).

enable GenAI developers to reach as many user companies as possible.

Users have not yet shown interest in GenAI the way that businesses have, but investments from large tech firms may expand the market for AI systems in the next five years. However, the point of expanding the market is also ensuring that the increasing amount of available data can be made suitable for the purpose of deep learning that is embedded in GenAI systems. This will also require developing algorithms that can separate the "signal" from the "noise" (i.e., distinguish reliable from unreliable data), as well as factually true information from misinformation. Users may flock to the technology if it shifts the power to innovate away from highly skilled technicians to less skilled individuals.

5.3. Scientific and artistic creativity and GenAI-enabled innovations

The experts in our Delphi study overwhelmingly expressed that scientific and artistic creativity will be enhanced and empowered through GenAI—and perhaps even be conceptualized differently compared to non-GenAI creativity. Their insights add to a long, multidisciplinary discourse started in the 1960s – across psychology (e.g., MacKinnon, 1965; Mednick, 1962), physiology (e.g., Levy, 1961; Rhodes, 1961) and sociology (e.g., Getzels & Jackson, 1961; Straus, 1968) – on why and how some individuals are more creative than others.

Innovation management research has traditionally conceptualized individual creativity as depending on intellectual abilities (e.g., intelligence, memory, the ability to look at problems in unconventional ways, the ability to recognize worthwhile ideas and articulate them to others), personality (e.g., openness to experience), knowledge (e.g., the amount of field-specific knowledge), motivation (e.g., mere enjoyment vs. extrinsic rewards) and the environment (e.g., whether the context is flexible or rigid about the space allotted to individuals to explore their ideas independently) (Amabile, 2018; Schilling, 2018). Interestingly, an important intellectual ability for creativity is individuals' ability to undertake a visual mental activity called primary process thinking (Suler, 1980). This process generally involves combining ideas that are not typically related, leading to what has been termed "remote associations" or "divergent thinking". While the best humans still outperform artificial intelligence in divergent thinking tasks (Koivisto & Grassini, 2023), most humans do not. Furthermore, as GenAI is endowed with better memory capacity and computational capabilities, it is likely that it will be: 1) more effective than humans in developing a larger network of possible associations; 2) faster than humans in searching for longer paths through the network of possible associations. On this basis, future research might examine if GenAI is likely to enhance or hasten the divergent thinking of creative individuals involved in the scientific or artistic domains.

More recently, some scholars have argued that AI itself can be creative in the sense of being capable of producing "highly novel, yet appropriate, ideas, problem solutions, or other outputs" (Amabile, 2020: p. 351). Therefore, future innovation management research might explore if and to what extent GenAI is creative itself and how GenAI creativity differs from human creativity in terms of its determinants. For instance, scholars might investigate: human vs. GenAI memory; human vs. GenAI ability to look at problems in unconventional ways; human vs. GenAI ability to analyze which ideas are worth pursuing; human vs. GenAI ability to articulate those ideas to others; and human vs. GenAI domain knowledge. New ideas might take the form of interesting questions rather than just solutions. GenAI might expand the set of suitable inquiries and alter how scientific and technical communities shape their research questions.

Obviously, GenAI has an advantage over humans insofar as it can absorb larger training sets that facilitate a more creative rationality (Forest & Faucheux, 2011) that is less bound, to borrow a term from Herbert Simon (Simon, 1984, 1991). This implies that scholars in innovation management will have the opportunity to extend the research stream on creative rationality (Forest & Faucheux, 2011) by embedding GenAI in their work.

Of course, creativity is not exclusively about the individuals who generate ideas; it is also about the audience(s) that receive and evaluate said ideas (see Mihály Csikzentimihalyi (1975) and his theory of flow). In other words, the success of new ideas and products enabled by GenAI might depend on the reception of various audiences, including consumers, domain gatekeepers and experts. This raises several questions: First, will GenAI-enabled innovation attract multiple audiences? If creative individuals (e.g., inventors, artists) want to ensure that their ideas are well received, they need to appeal to both key domain gatekeepers (Hirsch, 1972) and consumers. Indeed, creatives need a knowledge of both target audiences in order to determine whether they have the knowledge and skills to distinguish between good vs. bad work in the generative domains (e.g., generative music, generative chemistry, etc.). To this end, scholars will need to apply a social perspective to creativity.

Second, what judgmental heuristics will consumers use to interpret new ideas? Under the "effort heuristic" (Kruger et al., 2004), consumers assume that good (artistic) work takes time and effort, and therefore judge quality based on the effort of the creative individual or team. Under the "talent heuristic" (Cho and Schwarz, 2008), by contrast, consumers might conjecture that talented producers are faster (and need to invest less effort) than untalented producers at generating a product of comparable quality. This has implications for research: After all, GenAI-enabled innovations (new text, music, video, etc.) do not take much time to be created. If consumers adopt an "effort heuristic" (Kruger et al., 2004), they might infer that GenAI-enabled products are of low quality; but if they adopt a "talent heuristic", they might be surprised by the proficiency of the underlying algorithms. Future research should evaluate when and why consumers apply these heuristics to GenAI.

Third, how will organizational creativity be shaped by a blend of human and AI creativity? Organizational creativity depends on not only the individuals within an organization, but also the social and contextual factors (e.g., organizational structure, incentives, and routines) that shape how those individuals interact with each other (Woodman et al., 1993). Organizations' adoption of GenAI systems will likely modify how their employees interact with each other in creative activities and processes, with some of their creative work being offloaded onto said systems. Future scholars should explore these dynamics, extending extant research (e.g., Woodman et al., 1993) on organizational creativity to ascertain how those systems will affect organizational structures, incentives, and routines.

Fourth, is the new idea perceived as authentic regardless of its progenitor (a human vs. a GenAI system)? As the literature indicates, authenticity is a very complex concept (Lehman et al., 2019) with three broad signals: 1) consistency; 2) conformity; 3) connection. If authenticity is conceptualized as "consistency" between an entity's external expressions and its internal values/beliefs, then GenAI-enabled products/brands (and perhaps GenAI itself) will likely be personified. In this case, future research might look at different aspects of this personification process, such as how different stakeholders perceive identity. If authenticity is conceptualized as "conformity" (e.g., of an entity to the social category to which it has been assigned or claimed for itself), then future research should deal with how GenAI entities operate within existing categories (human-made vs. GenAI-made vs. hybrid products) and how audiences (consumers, gatekeepers, etc.) make authenticity attributions based on conformity to norms inherent in those categories (i.e., human innovation, GenAI-enabled innovation, hybrid innovation). Scholars may need longitudinal studies to assess how categories shift over time—for instance, in 20 or 30 years from now, the notion of hybrid human-GenAI innovation might become the "default". Lastly, if authenticity is conceptualized as a "connection" between an entity and a person, place, or time, then research will have to contend with the ubiquity of digital space and the decreasing relevance of provenance. As the spatial or temporal distance between an entity and its origin grows, it is possible that GenAI-enabled innovations can evoke authenticity through mere references to a person, place, or time of interest. Future research in innovation management should dig deeper into this complex expression of authenticity.

As suggested by the Delphi experts, traditional concepts of individual and organizational human creativity will likely be altered, but this will be more relevant for artistic creativity where physics and chemical laws (relevant for the hard science domains) do not constrain idea generation or implementation. Thus, the discussion related to judgemental biases and authenticity should be contextualized in terms of artistic vs. scientific creativity.

5.4. GenAI-enabled innovations and intellectual property

The majority of the experts participating in the Delphi study mentioned that GenAI will undermine our current conceptualizations of intellectual property (IP) in innovation management. According to several experts, traditional IP will be made obsolete by GenAI systems' ability to create new products in data-rich environments (Wedel & Kannan, 2016). On this front, future research may need to cultivate two complementary lines related to the inputs and outputs of GenAI systems (see Fig. 3).

As Fig. 3 illustrates, GenAI systems are trained on a range of data inputs—text, audio, video, etc. Some of these inputs might be protected by copyright and/or patent law. Once the training set is inputted into the GenAI system, the system cannot attribute content to legitimate authors or compensate them for the use of copyrighted content. This infringement of traditional copyright and/or patent law is no longer theoretical: As a recent class action lawsuit of artists against Stability AI, Midjourney, and DeviantArt (AI systems providers) shows (Brittain, 2023), using GenAI systems runs the risk of infringing on copyright and/or patent law if the GenAI firm did not legally license the intellectual property (IP). This translates into uncertainty about how value will be appropriated and by whom. Several IP law scholars and legal practitioners are currently dealing with these thorny issues (Samuelson, 2023). Unless traditional copyright/patent laws are modified, then the only lawful GenAI systems would be those trained on public domain work (i.e., work whose copyrights already expired) or under licenses. In the latter case, the licensing agreement should affect everyone (individuals and organizations) that use GenAI, including the entrepreneurs and companies integrating GenAI into their new products. This situation could limit the size of training sets, thereby preventing GenAI systems from working at full capacity. It is likely that a debate will emerge between two factions: on one hand, conservatives will defend extant copyright law; on the other hand, futurists/technologists will try to challenge traditional copyright law in the name of technological advancement. There might also be a third way, whereby a watershed date is determined, whereby policymakers shorten the duration of copyright (the current window typically covers 50 years until after the death of the author or copyright holder) or even establish a date after which traditional copyright law no longer applies to new intellectual work. As copyright laws vary from country to country, a few countries will likely modify their copyright laws before others, which could produce a disharmony that could negate extant international conventions (e.g., the Bern convention, the Universal Copyright Convention, the WIPO Copyright Treaty).

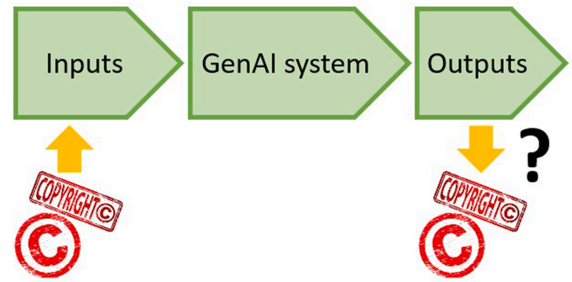

Fig. 3. Copyright issues pertaining to the inputs and outputs of GenAI systems supporting innovation activities and processes.

Considering the importance of training data to GenAI systems' performance, it is likely that companies that own/control large amounts of private data will be able to generate higher innovation value than organizations that do not own/control such data. This means that firms endowed with valuable, rare, inimitable, and non-substitutable private data will also be those that outperform rivals in terms of value creation and appropriation (generative AI algorithms being equal). This implies that companies that own/control data will gain a persistent innovation advantage over competitors (Cockburn et al., 2018)—an advantage that will not depend on economies of scale and network effects. This possibility calls for the application of the Resource-Based View (RBV) (Barney, 1991), the organizational capabilities framework (Helfat & Lieberman, 2002), and the dynamic capabilities framework (Teece et al., 1997) to GenAI-related innovation management studies.

There are just as many open questions surrounding the topic of outputs (Epstein et al., 2023). Who holds the copyright of a new product that was generated by a GenAI system? Is the copyright holder the prompt engineer who skilfully used the GenAI system? More generally, who will retain IP rights to the new products stemming from GenAI systems? Should copyrights be shared between the prompt engineer and the GenAI system? Who should get the royalties and in what form? How will new products stemming from GenAI be protected by IP laws? How shall business models be modified to reflect the creation of value through GenAI systems? Since GenAI is likely to generate new products and processes faster than other systems, how can patent offices accelerate their own workload in order to protect GenAI innovations?

As one US Delphi participant predicted, innovation management scholars may need to conceptualize novel forms/types of intellectual property (protection) that cover the outputs of GenAI. These might come in the form of new licenses and/or IP agreements. Furthermore, private organizations have fewer incentives than their public counterparts (e.g., universities or governments) to share innovation outcomes stemming from GenAI; disseminating the results to the wider community may be secondary to protecting their GenAI outputs. Different incentives will characterize the conduct of academic vs. private researchers and innovators. Hopefully, non-profit organizations that are leading and shaping most of the generative AI projects (e.g., OpenAI) will make their work and data accessible. As the innovations generated by both private and public organizations depend on the aggregation of data from disparate sources, it will be important for all sectors to develop attributional rules.

5.5. GenAI and new product development

The majority of our Delphi study participants argued that GenAI will change how management scholars construe NPD and NPD teams. Currently, the extant literature has identified three conflicting goals in NPD frameworks: 1) minimizing the development cycle time; 2) maximizing the product's fit with customer needs and requirements; and 3) compressing development costs (Schilling, 2008, 2023). Through GenAI, innovation managers may be able to achieve these three goals jointly without making significant tradeoffs. Respectively to each point, GenAI can potentially: 1) reduce the time for research and development; 2) support real-time testing of new products (and more generally, validate business model propositions); and 3) compress development costs through the use of digital prototypes. In these ways, GenAI might generate a breakthrough in research related to NPD acceleration (e.g., Nijssen et al., 1995; Schmenner, 1988), leading to novel models that go beyond the established frameworks of sequential, parallel, and partly parallel development processes (e.g., Griffin, 1992).

The literature has uncovered various tools in NPD processes – such as stage-gate processes (e.g., Cooper & Kleinschmidt, 1991), quality function deployment (e.g., Carnevalli & Miguel, 2008; Clausing & Hauser, 1988), failure modes and effect analysis, and computer-aided design and manufacturing (Aimar et al., 2019) – that can be significantly enhanced through GenAI systems. For example, GenAI systems could be used to augment the typical stage-gate process, bolster creative brainstorming sessions, or facilitate small-scale prototyping through digital rendering and 3D printing. Studying those applications can extend extant industry research on the relevance of GenAI in design and development (Brossard et al., 2020). With the aid of GenAI, innovation managers could validate their assumptions in near real-time, allowing them to more quickly pivot their business ideas into products/processes/business models. Examining those applications will significantly extend the extant literature on experimentation and validation (Thomke, 2020). Likewise, firms could leverage GenAI to make their new product testing more responsive to consumers' changing preferences and needs (Mariani & Wamba, 2020). We cannot discount that GenAI systems will also be used to generate customer personas and segments to simulate new product acceptance and adoption. More generally, the incorporation of GenAI into innovation testing and experimentation research will help extend the research stream on innovation analytics (Kakatkar et al., 2020; Mariani & Nambisan, 2021).

Another relevant issue is how GenAI can facilitate co-creation between companies and customers. In extant innovation management research, scholars have emphasized that involving customers in NPD is particularly important because they not only represent an information source, but also constitute actual co-developers of new products (e.g., through techniques such as beta testing and agile development; Cui & Wu, 2017). Several studies have suggested that firms should focus their development efforts primarily on the input of lead users (i.e., those who express needs earlier than the rest of the marketplace) rather than a large sample of customers (Herstatt & Von Hippel, 1992). To this end, GenAI allows a much smoother involvement of customers in NPD. For instance, conversational GenAI can learn from users, with conversational GenAI (e.g., ChatGPT, GPT-4) capable of using customers' inputs to form new text. This could open new research avenues, as GenAI systems might be progressively gain the ability to weigh users based on their demonstrated expertise with a certain category of products (Mariani & Nambisan, 2021) and thereby uncover lead users (Herstatt & Von Hippel, 1992). In short, GenAI has the potential to talk to a broader array of customers, and potentially distinguish between more advanced and novice users.

The literature has emphasized that NPD often involves blending departments and functions Schilling, 2023). Indeed, there is a rich research stream revolving around NPD team construction (e.g., optimal size, composition, etc.), structure (e.g., functional, lightweight, heavyweight, autonomous, etc.) and management (e.g., team leadership and administration). Not surprisingly, this literature has focused almost exclusively on human teams. However, as suggested by recent research (e.g., Leone et al., 2021; Paschen et al., 2020; Wamba-Taguimdje et al., 2020; Wamba, 2022) and our surveyed experts, humans and AI systems are increasingly collaborating to create value. Thus, GenAI-powered machines may soon be full-fledged members of NPD teams. In this vein, future research should explore the dynamics of different team configurations (e.g., human-only teams vs. human–machine hybrid teams) in order to better understand value creation. In summary, the introduction of GenAI into NPD will undeniably lead to a major shift in how innovation management scholars construe and conceptualize the NPD process and teams.

5.6. Multimodal/unimodal GenAI and innovation outcomes

Technically, GenAI systems can be unimodal vs. multimodal. The former work with one type of data input, while the latter generate outputs from various inputs (e.g., text, voice, audio, video, and pictures) (Cao et al., 2023). This technical distinction bears important implications for the type of innovation outcomes that firms achieve. For instance, because multimodal GenAI systems can blend multiple data types in unique ways, they can create richer, more interactive experiences that translate into greater user satisfaction and engagement. Leveraging that ability might extend marketing studies in the customer satisfaction research stream (Churchill & Surprenant, 1982), as well as enrich innovation management studies looking at how to maximize a product's fit with customer needs and requirements (Schilling, 2023).

Multimodal systems also have the advantage of allowing high personalization, which can help products better adapt to various audiences and channels. Scholars of innovation management should more thoroughly study the shift from mass-customization (Wang et al., 2017) to mass-personalization, regardless of the domain analyzed (manufacturing vs. service industries).

Lastly, multimodal GenAI can generate content that is contextually relevant. This might enhance virtual and augmented reality technologies, and the metaverse technologies more generally (Dwivedi et al., 2022). Given the previous premises, future research might test if multimodal GenAI systems produce a competitive advantage relative to their unimodal counterparts.

5.7. GenAI, agency and ecosystems

The Delphi study respondents suggested that the introduction and consolidation of GenAI systems is likely to produce a dense network of actors and stakeholders – not all of them human – that will increasingly collaborate in pursuit of innovative outcomes. By implication, GenAI-enabled innovation will happen through distributed agency, whereby agents can be humans and machines whose interactions trigger innovation processes. Future innovation management research will need to incorporate theoretical constructs that capture how the locus of innovation agency distributes across multiple actors (not only in terms of individual humans or machines, but also groups of humans and/or machines). In doing so, we encourage innovation management scholars to extend the notion that the locus of agency is distributed in digital environments (Nambisan, 2017).

According to this distributed agency perspective, GenAI is a complement to, rather than a substitute for, humans initiating, implementing, and managing innovation projects. Interesting questions to address here are: How will humans, organizations and GenAI systems interact in innovation projects and NPD? Will there be a prevalence of human vs. artificial agents in innovation projects and NPD? Will there be a hierarchy between human and GenAI agents in innovation projects and NPD? Will humans delegate computational tasks to GenAI systems and retain discretionary ones? Will humans (e.g., innovation managers) be able to maintain control over GenAI systems while interacting with them? Will that dynamic change over time?

A few of our experts mentioned that, as GenAI favors the tendency toward dispersed agents, researchers could build on theories of open innovation (Chesbrough, 2003; Chesbrough & Appleyard, 2007) to explore how the loosely coupled agents involved in innovation will interact with GenAI systems. It is highly likely that in the short-term, humans will use GenAI to augment their own capabilities (La Roche, 2017; Raisch and Krakowski, 2021). That said, human-GenAI interactions might evolve over time, leading to a decline of human involvement in innovation processes. Accordingly, evolutionary perspectives to innovation (Nelson & Winter, 1977, 2002; Staw, 1990) might shed light on the trajectory of human-GenAI interactions in the pursuit of innovation.

The intuition that innovation activities will involve a conspicuous number of loosely connected agents is compatible with the idea that innovation will unfold in business ecosystems where several human-GenAI interactions take place. Accordingly, future innovation management research on GenAI should build on business ecosystems research (Clarysse et al., 2014; Fuller et al., 2019; Iansiti & Levien, 2004; Zahra & Nambisan, 2012). After all, business ecosystems consist of a large number of loosely connected specialized agents who depend on each other for their mutual performance—whether through cooperation, competition or coopetition (Moore, 1993). They are balanced by a "keystone" company that invests in and integrates other participants' technological innovations while encouraging the development of platform infrastructures. There are several questions that scholars could address here: 1) How will GenAI and human agents interact with each other? 2) Will they adopt a competitive, cooperative or coopetitive mode of interaction? 3) Will interactions evolve over time and how? 4) Will interactions be predominantly horizontal or vertical)? 5) Will humans delegate most of the computational tasks to GenAI systems and retain discretionary ones? 6) Will humans (e.g., innovation managers) be able to preserve control on GenAI systems while interacting with them and will this change over time? 7) Will interactions enable the generation of less bounded and predefined innovation outcomes? 8) Is it more likely that the agent endowed with the best-performing GenAI system will also play the role of the "keystone" player?

5.8. Policymakers, lawmakers and anti-trust authorities in the regulation of GenAI-enabled innovation

The experts in the Delphi study highlighted that extant frameworks for regulating entities that pursue GenAI-enabled innovation should be updated, if not radically modified. On that point, legal scholars in the UK and US have spent the last decade calling for an Artificial Intelligence Development Act and the creation of government agencies to certify AI programs' safety (Etzioni and Etzioni, 2017). It seems clear that policymakers will play a critical role in shaping the regulatory environment for GenAI. The European Union appears to be a pioneer in this regard—having proposed the *AI Act* in 2021, which establishes a regulatory framework for the providers and professional users of AI across multiple sectors (all save for military/defence)—while most non-EU countries are lagging behind (Chatterjee & Sreenivasulu, 2022). The EU's framework classifies AI applications by their risk and regulates them accordingly; other countries (e.g., Brazil) seem to be following suit, which suggests that the AI Act may become a global standard (similar to the GDPR). That said, there are many open issues to address: First, it seems unclear if GenAI will be regulated differently from other forms of AI. As the outcomes of GenAI depend on the aggregation of data and content from multiple sources, policymakers will need to develop a new regulatory framework that can establish and enforce rules of credit and attribution. Intellectual property (IP) lawmakers will likely need to work alongside multidisciplinary groups of AI experts to design laws dealing with GenAI-related IP rights, which could effectively reshape—if not entirely rewrite—extant laws on data ownership (Cockburn et al., 2018: p. 41). For instance, if online consumer data belong solely to consumers, then firms could not use them for product innovation purposes. Second, amidst this uncertainty, firms should prepare internally to comply with new standards (Hine & Floridi, 2022). Some organizations will need to form ad hoc ethical GenAI committees that oversee the firm's compliance with standards and conformity assessments. Granted, the adoption of standards will be uneven across countries (and organizations), due to the speed at which different governments establish meaningful regulatory frameworks. Certainly, managers of organizations with a legal basis or subsidiaries in the EU will need to act fast in response to the AI Act, as well as recent and forthcoming developments in privacy law. Third, for the US specifically, patenting GenAI and machine learning algorithms was nearly impossible until a few years ago (Chisum, 1985; Chowdhury, 2022), but now innovators can patent the sequences of stages in the methods. Notably, Ian Goodfellow and his colleagues—who developed one of the architectures of GenAI (namely GANs)—recently secured patents for several GenAI algorithms. However, patent law does not make clear whether GenAI outputs (e.g., new molecules, text, videos, music, etc.) are patentable. Past episodes suggest that radical innovations in research techniques and tools—in tandem with patent offices' limited capacity and inconsistent (if not contradictory) court verdicts—can lead to long periods of uncertainty that undermine the issuance of new patents and inhibit research productivity. Certainly, patent law should be significantly extended and innovation management scholars could contemplate if and to what extent the outcomes of generative AI can be patented. Fourth, policymakers and regulators need to weigh the issues of algorithmic biases and consumer protection that accompany machine learning and deep learning. Case in point: Deepfakes can damage the reputation of both individuals and organizations; a global response is increasingly critical amidst the growing adoption of GenAI systems. Legal scholars have suggested passing legislation that addresses discrimination, libel, defamation, identity theft, fraud, impersonating (government) officials, counterfeit, and political risks (Ray, 2021; Westerlund, 2019; Wiles, 2023). Of course, such regulations need to be crafted carefully in order to be enforceable and acceptable (Farish, 2020). Moreover, international institutions should be set up and develop solid standards to regulate algorithmic biases, consumer protection and (especially) misinformation stemming from generative AI. Fifth, GenAI is going to make a huge impact on the worldwide economy in terms of innovation outcomes and productivity, but this will have the collateral effect of causing some organizational restructuring and, more worryingly, disruptions in the labor market. With AI already creating income inequalities (Kelly, 2021), it is urgent for lawmakers and trade unions to engage in a constructive conversation about policies – such as a universal basic income (Banerjee et al., 2019) – that can potentially offset the employment damage induced by AI in general and GenAI in particular. Sixth, the AI Act (AIA) imposes strict obligations for companies that develop, operate, and use AI systems, based on the risks associated with the AI system itself (Hickman & Petrin, 2021; WEF, 2022). Some commentators have emphasized that the AI Act lacks effective enforcement structures (Ebers et al., 2021), does not accurately define AI, and does not allocate responsibility for the detrimental consequences of AI usage (Smuha et al., 2021). Nonetheless, the Act imposes burdens on companies that develop, operate or use GenAI systems to innovate, as violating the Act brings about penalties of up to €40 million, or 7 % of a company's annual global revenue, whichever is higher (for reference, this exceeds the GDPR's fining range). More specifically, the penalties for (Gen)AI foundation model providers who breach the AI Act could be about €10 million (or 2 % of annual revenue, whichever is higher). Clearly, AI-dependent companies will need to allocate resources to be compliant with the AIA (Gragousian, 2022). That allocation will likely be easier for large corporations, but represent a burden on SMEs, which could facilitate an environment where only resource-rich firms can afford to incorporate GenAI into their innovation activities. Overall, the aforesaid constraints might stifle AI-driven innovation.

Despite these regulatory questions, there will be a race for GenAI within many industries (such as pharma, biotech, media, and entertainment). Multiple organizations will seek to establish a proprietary advantage in terms of data and algorithms, which has implications for competition policies. Those organizations with better data in a specific application field (e.g., oncology or autonomous driving or e-commerce) will likely have a first-mover advantage; as such, they can erect both a data-driven barrier to entry and a "deep-learning-driven barrier to entry" (Cockburn et al., 2018: p. 142), To counteract the risk of market dominance, antitrust authorities should put those companies on their radar while encouraging data sharing and data openness to ensure that all economic actors can benefit from generative AI systems.

To summarize, future innovation management research might need to incorporate theoretical constructs that build on the legal and antitrust literatures. The goal should be to generate insights into the policies, laws and regulations that will be necessary to address issues such as the use/misuse of GenAI for innovation or the uneven ownership and control of data across multiple application settings.

5.9. Misuse and unethical use of GenAI leading to biased innovation

Like any technology, GenAI can be adopted for unethical, unfair, immoral, and illegal purposes—and those uses could bias innovation, according to our Delphi participants. One of more cited examples in this regard is the deepfake, which can be defined as "digitally manipulated synthetic media content (e.g., videos, images, sound clips) in which people are shown to do or say something that never existed or happened in the real world" (Mustak et al., 2023: p. 1). On one hand, deepfakes generate business opportunities (e.g., cutting costs for actors and journalists; creating digital brand ambassadors; shaping inexpensive learning environments; developing novel economic offerings based on deepfakes to personalize products and brands; improving virtual customer journeys) (Perez-Vega et al., 2021), as well as support business model innovation (Kietzmann et al., 2020). For instance, the South Korean TV broadcaster MBN used a deepfake of its news anchor-man Kim Joo-Ha (Foley, 2022) and found that the deepfake worked well for reporting breaking news. On the other hand, deepfakes pose several challenges, including: a reduction of jobs in many industries such as media and entertainment; damages to the reputation, image and trustworthiness of individuals, professionals, and organizations; bias in market competition; the manipulation of public opinion by criminals and terrorists; or the creation of misinformation by hackers, rival companies, and governments (Marcus, 2022). In the case of malicious deepfakes, it is very difficult for victims to demonstrate a privacy breach (Graham et al., 2021). Many countries still struggle with adequately addressing privacy issues (Saura et al., 2022), much less defining a regulatory framework that offers protection against deepfakes (Mustak et al., 2023).

Apart from deepfakes, the content generated by GenAI is often of debatable quality. For instance, Stack Overflow (one of the most relevant question-and-answer websites for software developers) was recently inundated by ChatGPT-generated submissions (Mark, 2022). This led the website to impose a temporary ban on those submissions, as "the average rate of getting *correct* answers from ChatGPT is too low, the posting of answers created by ChatGPT is *substantially harmful* to the site and to users who are asking or looking for *correct* answers." For Stack Overflow—more so than even online review travel websites (e.g., TripAdvisor) or e-commerce websites (e.g., Amazon)—having correct/authentic posts is of paramount importance. If the website is inundated by incorrect code examples, the website will lose users engaged in programming and this might generate detrimental consequences for developers' productivity, professionalism, and reputation. This is also why some AI vendors are engaging with the production of machine learning operations ("MLOps") to monitor the inaccuracy of predictions and possibly enhance them over time. These issues speak to a more general challenge for GenAI systems: on one hand, the poisoning of their datasets by unethical influencers, marketers and even criminals for the purpose of influencing public opinion (Lobschat et al., 2021; Wirtz et al., 2023); on the other hand, the biased learning that could stem from GenAI systems interacting with users that display toxic or undesirable behaviors (Floridi & Chiriatti, 2020). These risks highlight a need for more corporate digital responsibility (Lobschat et al., 2021).

Lastly, GenAI models might be biased against certain groups and individuals (Akter et al., 2021; Mittelstadt et al., 2016) based on the data they were trained on. Biased results are likely to occur if the training data have not been carefully checked and if the GenAI algorithms lack ethical controls. To counteract this issue, firms will need to establish an AI ethics board that evaluates the ethicality of training data and algorithms (Fosso Wamba & Queiroz, 2021; Tsamados et al., 2021), or at least strives to guarantee transparency. That step is critical for ensuring GenAI-enabled innovations do not disproportionally benefit some stakeholder groups at the expense of others. Overall, it seems that future innovation management research might want to incorporate theoretical concepts and constructs that build on information ethics and information philosophy (e.g., Floridi, 2013, 2023) as well as innovation sociology (Gopalakrishnan & Damanpour, 1997) and law. Such efforts could generate insights on principles and guidelines that ensure that GenAI does not bias or ethically affect innovation outcomes.

5.10. Organizational design and boundaries for GenAI-enabled innovation

Most of the Delphi participants mentioned that GenAI will profoundly influence organizational design and boundaries. Some authors (Benbya et al., 2020) have argued that AI will lead to modifications in authority arrangements, coordination, and valuation schemes, causing radical industrial transformations, and others have pointed to changes in governance mechanisms (Schneider et al., 2022). Regarding authority arrangements, the introduction of GenAI will redefine the notions of knowledge and expertise. Workers in general (and scientists and artists in particular) will have to be proficient in using GenAI systems in order to complete innovation projects, but most will not need deep technical knowledge of the subject matter (science or art) in order to innovate inside the company. Instead, they will just need the support of computer and data scientists. The idea of upskilling may largely be replaced by training scientists and artists to interact with GenAI systems. This means that inside R&D functions and research labs, those with knowledge of GenAI systems will gain control over work design. At the C-suite level, incumbent CTOs and CIOs will need to coordinate with Chief Data Officers when creating and developing a generative GenAI strategy. This arrangement will likely generate tensions and conflicts that the CEO will need to manage.

Regarding coordination, the deployment of GenAI will likely cause many work tasks to be atomized into smaller modular subtasks that can be outsourced—potentially to a micro task digital marketplace (e.g., Amazon Mechanical Turk, Jovoto, Clickworker, Prolific, Upwork, Crowd Guru) or any GenAI system (e.g., ChatGPT, Dall-E 2, Stable Diffusion, Midjourney). Over the last few years, different organizations have set up internal organizational roles (e.g., an AI manager or an AI champion) and structures (e.g., AI Center of Excellence) to govern AI projects. GenAI projects will likely engender a similar response. However, there are several questions that arise: i) How will incumbent innovation managers interact with the new GenAI-related roles? ii) Will incumbent innovation managers be allowed to interact with GenAI systems? iii) Will tensions arise between incumbent innovation managers and the new GenAI-related roles, and who will manage those tensions? In general, incumbent managers will need to start collaborating with experts in digital technologies (including data analytics, machine learning, deep learning, and GenAI systems more generally) and tailor their operations to suit those interactions. Organizations may also need to create new departments—either within the traditional R&D function or perhaps as cross-functional centers—that can support the firm's innovation efforts. In multi-national firms, the R&D department might establish an overarching GenAI platform that serves foreign subsidiaries (Ferraris et al., 2021).

Regarding valuation schemes, the way performance is being assessed is changing, because for instance employees are evaluated by ML algorithms, with HR managers lacking an ad hoc knowledge of the variables included in evaluation models. Overall, this will impact how firms manage their human resources. In relation to industrial transformations, GenAI may render the boundaries between industries more porous and less distinct. For instance, many traditional manufacturing firms (e.g., General Electric) are already becoming providers of solutions and services rather than products. The move to a service model is significantly enabled by digital technologies in general (Harrmann et al., 2023) and by AI in particular. Relatedly, GenAI may obscure the lines between competitors, suppliers, customers, potential entrants, and substitutes. Thus, innovation management scholars will need to concentrate on establishing design principles and guidelines for work tasks and incentives within organizations that adopt GenAI. Moreover, researchers can build on industrial organization theories to better delineate how the boundaries between organizations and industries might shift and evolve in the wake of GenAI.

6. Theoretical contributions

This study makes several general contributions to the innovation management literature—and more specifically to the nascent research stream at the intersection of GenAI and innovation management. First, we synthesized the academic literature with the results of a Delphi survey of leading (innovation) management scholars, with the goal of outlining the state of the field and future research opportunities. To the best of our knowledge, this is the first study to survey innovation management experts on the topic of GenAI in innovation management. Our work addresses recent calls for more research on the role of AI in innovation contexts (e.g., Cockburn et al., 2018; Mariani et al., 2023).

Second, our study identified 10 themes that can inform future research developments at the intersection of GenAI and innovation management: 1) Gen AI and innovation types; 2) GenAI, dominant designs and technology evolution; 3) Scientific and artistic creativity and GenAI-enabled innovations; 4) GenAI-enabled innovations and intellectual property; 5) GenAI and new product development; 6) Multimodal/unimodal GenAI and innovation outcomes; 7) GenAI, agency and ecosystems; 8) Policymakers, lawmakers and anti-trust authorities in the regulation of GenAI-enabled innovation; 9) Misuse and unethical use of GenAI and the generation of biased innovation; and 10) Organizational design and boundaries for GenAI-enabled innovation. Interestingly, several of these themes are intertwined from a conceptual viewpoint: For instance, the three themes of GenAI-enabled creativity, intellectual property and new product development share an emphasis on individuals and organizations trying to create ("creativity" and "new product development" themes) and appropriate value ("intellectual property" theme) by using GenAI systems to support innovation decisions and activities. By discussing the 10 themes in relation to the extant literature and theories, we have made several contributions to the innovation management field. For instance, while discussing the theme of dominant designs, we expanded innovation management theorizing by applying or extending established frameworks (Anderson & Tushman, 1990; Utterback & Abernathy, 1975). In relation to the theme of GenAI and creativity, we connected several concepts pertaining to different disciplines such as psychology (e.g., Csikszentmihalyi, 1975, 1997; MacKinnon, 1965; Mednick, 1962; Suler, 1980), physiology (e.g., Levy, 1961; Rhodes, 1961) and sociology (e.g., Getzels & Jackson, 1961; Straus, 1968). In that way, we introduced novel reflections on how innovation management research can move beyond recent notions of AI creativity (Amabile, 2020), thus opening up novel intellectual reflections.

Third, by shedding light on relevant themes, this paper can help innovation management researchers achieve more conceptual clarity regarding GenAI. That understanding will hopefully facilitate a more consistent and connected body of knowledge on innovation (management) studies revolving around GenAI. This significantly extends recent innovation management research (e.g., Mariani et al., 2023) that has reviewed AI-related innovation management research.

Fourth, our study suggests that academic research on GenAI in innovation management is in a very embryonic stage, whereas industry research is a little further along thanks to work done by Gartner (Wiles, 2023) or research funded by tech giants such as Meta and IBM (IBM, 2022). We hope that our preview of critical themes will help shape future research agendas in innovation management.

Lastly, this work developed directions and guidelines for future scholarship (reported in the different subsections of the Discussion section) by identifying research gaps and unanswered research questions. We hope that our work inspires additional inquiries in this domain and ultimately encourages the next generation of innovation management scholars to address important scientific challenges.

7. Conclusion

Generative AI (GenAI) is one of the most promising and fascinating forms of AI from an innovation management perspective. For that reason, researchers need to clearly understand how far the field has come and what possible directions it could follow. To that end, we combined a literature review with a a Delphi study of leading scholarly experts in GenAI. They provided a preview of 10 major research themes that innovation management scholars will need to address in the near future. Equipped with these insights, researchers will hopefully achieve more conceptual clarity regarding GenAI and work to build a more consistent and connected body of knowledge on the benefits and drawbacks surrounding GenAI.

This study is not without limitations. First, our sample of experts for the Delphi study was relatively small, although still notably larger than other recent studies of this type. For instance, the first and second rounds of Johnson et al.'s (2021) study only received 11 responses and 5 responses, respectively, but they nonetheless maintained that "Delphi studies are fundamentally different to, and should not be confused with, conventional statistical sampling and inferences techniques" (p. 107). Second, our identified research themes are not necessarily exhaustive. However, we are confident that they provide a suitable preview of future research lines. Ultimately, we hope to inspire researchers to critically reflect on the open questions we raise here and produce groundbreaking research in the innovation management field.

CRediT authorship contribution statement

Marcello Mariani: Writing – review & editing, Writing – original draft, Visualization, Supervision, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Yogesh K. Dwivedi:** Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

Table A1
Background to selected Delphi arguments.

#	Theme	Delphi argument	References or interviews
1	1	GenAI will not lead to the conceptualization of innovation types that go beyond extant innovation taxonomies (e.g., product/process, radical/incremental, architectural/component, etc.)	Interviews
2	1	Business model innovation might be significantly modified by the presence of GenAI	Kanbach et al. (2023), Akter et al. (2023)
3	2	A dominant design among GenAI systems has not emerged yet	Serrano (2023), interviews
4	2	The evolution of GenAI systems can be captured through extant technology evolution frameworks	Agarwal & Kapoor (2023), interviews
5	3	GenAI-enabled scientific creativity will be conceptualized differently than traditional scientific creativity	Amabile (2020), interviews
6	3	GenAI-enabled artistic creativity will be conceptualized differently than traditional artistic creativity	Amabile (2020), interviews
7	4	GenAI will lead to the conceptualization of novel forms/types of intellectual property (protection) in innovation management	Peres et al. (2023), interviews
8	4	GenAI will undermine the way we currently conceptualize intellectual property in innovation management	Peres et al. (2023), interviews
9	5	GenAI will modify the way we currently conceptualize deliberate vs. emergent strategies in New Product Development	Interviews
10	5	GenAI will change how management scholars construe and conceptualize the New Product Development process	Just et al. (2023), interviews
11	5	GenAI will change how management scholars construe New Product Development teams	Interviews
12	5	GenAI will change how management scholars construe and conceptualize experimentation and validation	Kanbach et al. (2023)
13	5	GenAI will change how management scholars construe and conceptualize new product testing	Kanbach et al. (2023)
14	6	Multimodal GenAI is likely to have a more positive influence on the adopting firm's competitive advantage than unimodal GenAI systems	Interviews
15	6	Multimodal GenAI is likely to have a more positive influence on the adopting firm's innovation performance than unimodal GenAI systems	Interviews
16	7	GenAI will make innovation management research on platform ecosystems more relevant than before	Akter et al. (2023)
17	7	GenAI-enabled innovation is more likely to be an open, rather than closed, form of innovation	Interviews
18	7	GenAI will change how innovation management scholars make sense of agency of innovation activities and processes	Interviews
19	7	Human-GenAI interactions will change innovation activities and processes	Hendriksen (2023)
20	8	Policymakers and lawmakers will need novel frameworks to regulate GenAI-enabled innovation	Interviews
21	8	Anti-trust authorities should be equipped with new frameworks to enforce regulations related to GenAI-enabled innovation	Interviews
22	9	The misuse of GenAI can generate biased innovation outcomes	Peres et al. (2023), interviews
23	9	The unethical use of GenAI can generate innovation outcomes that benefit only a subset of stakeholders	Peres et al. (2023), interviews
24	10	GenAI is likely to modify organizational boundaries	Interviews
25	10	GenAI is likely to modify organizational design and organizational coordination	Interviews

Table A2
Aggregated results from Round 1 (common sized values).

#	Theme	Delphi argument	Strongly disagree	Somewhat disagree	Neither agree or disagree	Somewhat agree	Strongly agree	Unable to comment	Number of Opinions
1	1	GenAI will not lead to the conceptualization of innovation types that go beyond extant innovation taxonomies (e.g., product/process, radical/incremental, architectural/component, etc.)	0.0 %	5.3 %	10.5 %	31.6 %	52.6 %	0.0 %	100.0 %
2	1	Business model innovation might be significantly modified by the presence of GenAI	0.0 %	0.0 %	11.1 %	38.9 %	44.4 %	5.6 %	100.0 %
3	2	A dominant design among GenAI systems has not emerged yet	5.3 %	0.0 %	0.0 %	84.2 %	10.5 %	0.0 %	100.0 %
4	2	The evolution of GenAI systems can be captured through extant technology evolution frameworks	0.0 %	0.0 %	5.9 %	35.3 %	52.9 %	5.9 %	100.0 %
5	3	GenAI-enabled scientific creativity will be conceptualized differently than traditional scientific creativity	0.0 %	22.2 %	11.1 %	55.6 %	5.6 %	5.6 %	100.0 %
6	3	GenAI-enabled artistic creativity will be conceptualized differently than traditional artistic creativity	0.0 %	10.5 %	15.8 %	63.2 %	5.3 %	5.3 %	100.0 %
7	4	GenAI will lead to to the conceptualization of novel forms/types of intellectual property (protection) in innovation management	5.3 %	15.8 %	5.3 %	36.8 %	31.6 %	5.3 %	100.0 %
8	4	GenAI will undermine the way we currently conceptualize intellectual property in innovation management	5.3 %	21.1 %	5.3 %	36.8 %	26.3 %	5.3 %	100.0 %
9	5	GenAI will modify the way we currently conceptualize deliberate vs. emergent strategies in New Product Development	16.7 %	44.4 %	5.6 %	16.7 %	11.1 %	5.6 %	100.0 %

(continued on next page)

Table A2 (*continued*)

#	Theme	Delphi argument	Strongly disagree	Somewhat disagree	Neither agree or disagree	Somewhat agree	Strongly agree	Unable to comment	Number of Opinions
10	5	GenAI will change how management scholars construe and conceptualize the New Product Development process	5.6 %	33.3 %	11.1 %	22.2 %	22.2 %	5.6 %	100.0 %
11	5	GenAI will change how management scholars construe New Product Development teams	0.0 %	5.6 %	11.1 %	44.4 %	33.3 %	5.6 %	100.0 %
12	5	GenAI will change how management scholars construe and conceptualize experimentation and validation	0.0 %	5.9 %	11.8 %	41.2 %	41.2 %	0.0 %	100.0 %
13	5	GenAI will change how management scholars construe and conceptualize new product testing	0.0 %	5.9 %	11.8 %	35.3 %	47.1 %	0.0 %	100.0 %
14	6	Multimodal GenAI is likely to have a more positive influence on the adopting firm's competitive advantage than unimodal GenAI systems	0.0 %	5.9 %	11.8 %	47.1 %	17.6 %	17.6 %	100.0 %
15	6	Multimodal GenAI is likely to have a more positive influence on the adopting firm's innovation performance than unimodal GenAI systems	0.0 %	5.9 %	11.8 %	52.9 %	11.8 %	17.6 %	100.0 %
16	7	GenAI will make innovation management research on platform ecosystems more relevant than before	0.0 %	5.6 %	5.6 %	33.3 %	38.9 %	16.7 %	100.0 %
17	7	GenAI-enabled innovation is more likely to be an open, rather than closed, form of innovation	16.7 %	22.2 %	16.7 %	16.7 %	22.2 %	5.6 %	100.0 %
18	7	GenAI will change how innovation management scholars make sense of agency of innovation activities and processes	0.0 %	5.3 %	21.1 %	31.6 %	36.8 %	5.3 %	100.0 %
19	7	Human-GenAI interactions will change innovation activities and processes	0.0 %	0.0 %	5.6 %	44.4 %	50.0 %	0.0 %	100.0 %
20	8	Policymakers and lawmakers will need novel frameworks to regulate GenAI-enabled innovation	0.0 %	5.6 %	0.0 %	33.3 %	50.0 %	11.1 %	100.0 %
21	8	Anti-trust authorities should be equipped with new frameworks to enforce regulations related to GenAI-enabled innovation	0.0 %	5.9 %	23.5 %	52.9 %	11.8 %	5.9 %	100.0 %
22	9	The misuse of GenAI can generate biased innovation outcomes	0.0 %	17.6 %	11.8 %	52.9 %	11.8 %	5.9 %	100.0 %
23	9	The unethiical use of GenAI can generate innovation outcomes that benefit only a subset of stakeholders	0.0 %	5.6 %	11.1 %	44.4 %	33.3 %	5.6 %	100.0 %
24	10	GenAI is likely to modify organizational boundaries	0.0 %	0.0 %	5.6 %	44.4 %	50.0 %	0.0 %	100.0 %
25	10	GenAI is likely to modify organizational design and coordination	0.0 %	0.0 %	5.9 %	47.1 %	47.1 %	0.0 %	100.0 %

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