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ORIGINAL ARTICLE

The Role of Artificial Intelligence in the Ideation Process

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ABSTRACT

The growth of Artificial Intelligence (AI) has important implications for business in general and innovation in particular. Ideation is the start of the innovation process. The authors review three fields of AI in ideation: identification and analysis of new opportunities, idea generation, and idea screening and idea selection. The results of the review are as follows. First, whereas in the past researchers highlighted the importance of industry characteristics and market stability, the authors now emphasize the importance of firm culture in driving innovation. AI will mediate this relationship. Second, across all stages, AI will improve efficiency, speed, and cost of ideation. Third, in opportunity identification, considerable progress has occurred in analyzing text and image; research on video and audio is relatively scarce. Fourth, in idea generation, AI increases the average creativity of ideas; however, the effect of AI on the generation of top ideas is conflicting. Fifth, AI assists very well in idea screening, but does not do a good job yet in idea selection. Sixth and most importantly, research remains in the early stages and will rapidly improve in the future. Thus, AI has the potential to radically transform ideation.

1 | Introduction

Innovation fosters the growth and success of individuals, firms, and even nations (Rubera and Kirca 2012; Tellis 2012; Tellis and Rosenzweig 2018). Innovation is the process of bringing new products and services to market (Hauser et al. 2006). Innovation can change existing markets or obsolete them by creating new ones. Ideation is the first step in innovation. An *idea* is a basic unit of thought that can be either visual, concrete, or abstract. *Ideation* is the process of generating, developing, and communicating new ideas (Jonson 2005).

Artificial Intelligence (AI) is a radically new technology that may have great promise in ideation. For the current article, we broadly define AI as "Any program or method that automates and derives 'intelligence' from data or applies intelligence to data." This definition includes, among others, methods like Large Language Models (LLM), Machine Learning (ML), Deep Learning, Neural Networks, Reinforcement Learning, and Natural Language Processing (see Davenport et al. 2020; for a more recent overview). The number of publications with AI, in all business fields, has skyrocketed. One promise of AI is that managers and researchers can perform existing business tasks better, faster, and cheaper than prior manual approaches. The literature focuses on how AI increases firms' efficiency and productivity (Coyle and Jones 2024; Davenport and Ronanki 2018; Huang and Rust 2021, 2022; Summerfield 2021). Yet, while there have been high-quality overviews in other subareas of business (Agrawal et al. 2018; Grewal et al. 2021, 2022; Guha et al. 2021, 2023; Haenlein and Kaplan 2019; Hermann and

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Summary

- While past research emphasizes the importance of market stability, industry characteristics, and firm culture in shaping radical (vs. incremental) innovation, the role of firm culture is expected to become even more critical in the age of AI. This is because AI will influence the relationship between firm culture and radical (vs. incremental) innovation. Therefore, managers should focus on building a culture that fosters innovation.
- In the early stages of the ideation process:
  - AI enhances the speed, efficiency, and cost-effectiveness of ideation. Managers should leverage AI tools to accelerate and scale the ideation process. They should stay adaptive because AI in ideation evolves rapidly.
  - AI improves the average creativity of generated ideas, but research is conflicting on whether it enhances the creativity of top ideas. Unless conclusive evidence shows that AI outperforms humans for all types of innovation, managers should continue to identify exceptional human talent.
  - AI performs well in idea screening but to date fails to deliver convincing results in idea selection. Managers should combine AI-driven insights with human judgment to ensure that they do not overlook high-quality ideas.

Puntoni 2024; Kopalle et al. 2022; Kopalle et al. 2024), one neglected area is the use of AI in ideation. This is the focus of the current review.

This review will propose a theoretical framework of the role of AI in ideation, summarize important findings, and highlight future research opportunities. We collect, assess, and structure existing research at the intersection of AI and ideation. We complement these findings from the literature with case studies, if appropriate. The aims of this article are to (a) develop a theoretical model that helps us to assess the role of AI in ideation, (b) provide an overview of the literature on the effects of AI in ideation, (c) identify potential generalizations, and (d) highlight potential future research directions.

The study arrives at the following findings. First, whereas in the past researchers highlighted the importance of industry characteristics and market stability, the authors now emphasize the importance of firm culture in driving innovation. AI will be an important mediator in this relationship. Second, across all stages, AI will improve efficiency, speed, and cost of ideation. Third, in opportunity identification, considerable progress has occurred in analyzing text and image; research on video and audio are relatively scarce. Fourth, in idea generation, AI increases the average creativity of ideas; however, the effect of AI on the generation of top ideas is conflicting. Fifth, AI assists very well in idea screening, but does not do a good job yet in idea selection. Sixth and most importantly, research remains in the early stages and will rapidly improve in the future. Thus, AI has the potential to radically transform ideation.

We build the rest of the manuscript as follows.

Section 2 presents our framework on AI in innovation across firms. Section 3 presents the innovation process within firms in the presence of AI with a special focus on ideation. In the following sections, we classify this article according to the stages of ideation. Section 4 presents the identification of new product opportunities. Section 5 deals with idea generation. Section 6 presents approaches related to idea screening and idea selection. This article ends with a discussion in Section 7.

2 | Theoretical Background of AI in Innovation

Figure 1 presents a theoretical framework of the role of AI in innovation.[1] AI has the potential to substantially alter relationships between variables that have long been generally accepted. In our case, the relationship that AI affects is the one between firm culture and type of innovation. Whereas prior research has emphasized the role of industry and market characteristics, we propose that the most important driver of innovation is firm culture. We next discuss the drivers of innovation.

2.1 | Main Factors

2.1.1 | Type of Innovation

Prior research studied differences between incremental and radical innovation (Chandy and Tellis 1998). Incremental innovation occurs constantly. It is the process by which firms daily improve products and services for consumers. Examples include more comfortable seats for autos, lower heat given off by light bulbs, or 1-day delivery for mail order.

In contrast, radical innovations are rare but transform markets. Examples are Tesla's electric car, the blockchain technology first implemented by Bitcoin (Nakamoto 2008), Ethereum's smart contracts, or 3D printing in prototyping or prosthetics. Radical innovations involve fundamental changes in the platform technology on which current firms serve customers and current markets exist. The perennial paradox in innovation is the tension between focusing on constant incremental innovation without being blinded to the arrival of radical innovations. In the current state of progress, AI is better at incremental rather than radical innovations. However, we expect that in the future AI will also contribute to radical innovations.

Prior research suggests that industry characteristics and market volatility are important drivers of innovation. However, recent research suggests that the most important driver of innovation is the culture of the firm (Rubera and Kirca 2012; Tellis 2012; Tellis et al. 2009).

2.1.2 | Firm Culture

Culture consists of three essential traits: willingness to cannibalize current successful products, future market focus, and risk tolerance. These traits in turn are driven by three practices

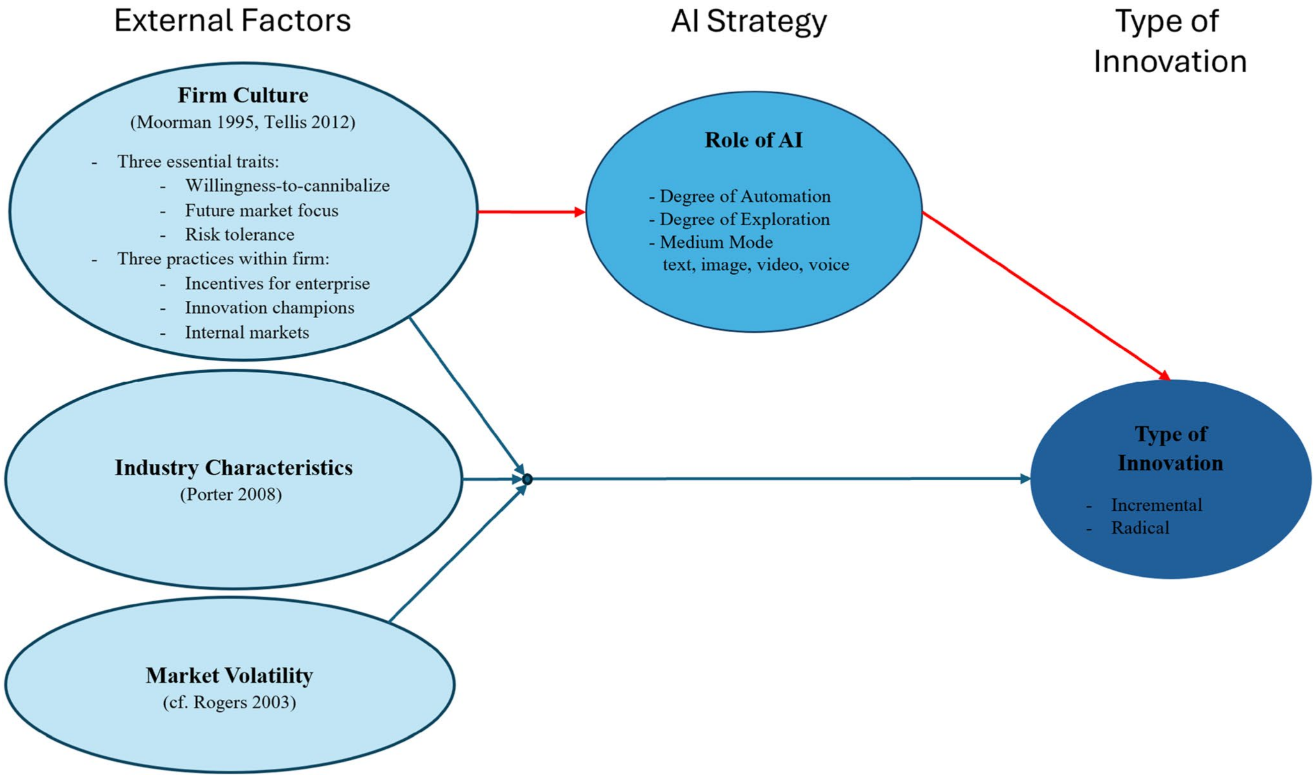

FIGURE 1 | AI affects the relationship between firm culture and type of innovation.

within the firm: incentives for enterprise, internal competition, and supporting innovation champions (Tellis 2012; also see Moorman 1995). Firms that score high on the six dimensions have an innovation-centric culture.

Firms should display the willingness-to-cannibalize (Chandy and Tellis 1998) their current products—including their best-selling products—by introducing radical innovations that compete against their own products (Govindarajan et al. 2011). This trait is the opposite of what firms generally do, which is to protect their best-sellers. For example, Kodak owned most of the technology for digital cameras. By clinging to their previously successful analogue technology, they lost the camera market.

Firms should focus on future markets, that is, firms should prioritize the long-term view over short-term profits. Firms can achieve this via investments in R&D and by anticipating future market trends. To anticipate future market trends, they can scan technological developments, patents (Grashof and Kopka 2023), and lead users (Urban and von Hippel 1988). For example, in the 1970s, Xerox had many of the revolutions of the computer age, such as the desktop computer, laser printer, and Windows display. But they focused on selling copiers and lost sight of the future digital revolution.

Innovations have a high failure rate. Thus, playing the innovation game requires a high tolerance for failure. So, being innovative involves embracing risk. While many firms punish failure, innovative firms see failure as a learning opportunity. This is particularly the case for bold ideas that may (or very often, may not) lead to radical innovation. Therefore, firms should cultivate a culture that allows experimentation (Chandy and Tellis 1998; Tushman and O'Reilly 1996). This mindset enables employees to operate at or beyond the boundaries of knowledge. Firms like 3M or Google allow employees to invest a percentage of their work time on projects that may not be related to their core tasks.

Most firms reward seniority and age. This policy engenders loyalty but not innovativeness. However, innovative firms set their incentives for producing innovations even at the cost of many failures. In particular, this practice involves strong rewards for success but weak penalties for failure (Amabile and Pratt 2016; Tushman and O'Reilly 1996). Such asymmetric incentives encourage employees to think creatively, come up with ideas, and take ownership of their ideas. These ideas then can receive funding so that their owners can develop ideas into innovations—and compete with other ideas.

Firms should empower innovation champions. Innovation champions are employees who are passionate about new ideas and have the influence and access to resources that allow them to advocate and receive support for radical innovation projects (Howell and Higgins 1990). This concept is closely related to existing research on serial ideators (Griffin et al. 2012), lead users (Von Hippel 1986), or consumers high in emerging nature (Hoffman et al. 2010). Such innovators are distinctive in their knowledge and personalities (Hauser et al. 2006; Peres et al. 2010).

Firms should create internal markets, that is, systems in which ideas compete for resources. Firms can do so by running innovation tournaments (Camacho et al. 2019; Terwiesch and Ulrich 2009), prototype races, or independent divisions that compete for the same market. In Google's Project X, in some cases, multiple teams work on the same overarching challenge (e.g., widespread internet access) from different competing technological perspectives (e.g., balloons vs. satellites vs. drones). Internal markets encourage risk-taking and fast processes and reduce lengthy bureaucratic processes. Markets also ensure that the best ideas receive funding and are developed into innovations. This allows firms to remain agile and to quickly react to changes in the environment.

Overall, culture is an important factor in the context of innovation (Tellis 2012; Tellis et al. 2009) and marketing in general (Moorman 1995; Moorman and Day 2016).

With respect to the effect of firm culture on radical versus incremental innovation in times of AI, we see the following research challenge.

Future research could determine which of the two patterns will be more common in times of AI.

While literature provides conflicting perspectives with respect to size (also see Benbya et al. 2020), a look at the industry may provide relevant information. In the automotive industry, for several decades, incumbents have developed incremental innovations like more efficient motors. However, the radical innovations of an all-electric vehicle and a new user experience via a completely different software were developed by an outsider, Tesla. Likewise, in the AI industry, incumbents like IBM have provided incremental innovations in the areas of machine learning for years, but the radical breakthrough of LLMs originated in OpenAI, a smaller, outsider firm.

2.1.3 | Industry Characteristics

Porter (2008, 32) studies the intensity of rivalry among existing competitors in an industry. Rivalry is higher in an industry with many (vs. few) similar (vs. dissimilar) competitors, with high fixed costs, and with a low degree of product differentiation. While Porter argues that rivalry takes many forms, including price discounting, new product introductions, or advertising campaigns, the impact of rivalry on innovation has at best been studied in scattered studies.

On the one hand, in high-rivalry settings in which resources are scarce, risk averse firms may prefer defensive strategies, in which they continuously refine their capabilities and come up with incremental innovations (Danneels 2002) that assure customer loyalty (Schilling 2018). On the other hand, taking the risk and investing in radical innovations may allow firms to create unique products that stand out (Tushman and Anderson 1986) and, therefore, attract more consumers.

2.1.4 | Market Volatility

Low market volatility may lead to inertia among firms. Abernathy and Utterback (1978) argue that in mature industries with low volatility, firms focus on increasing efficiency, for example via process innovation, to increase their profits. In contrast, if market volatility is high, for example in the oil industry, firms may break inertia by investing to change things. Customer preferences may be less stable and more likely to change. These changes in preferences lead to discontinuity in consumers thought processes and consequently in their adoption behavior (Rogers 2003). On the other hand, Christensen (1997) argues that firms in markets with low market volatility often invest in radical innovations (also see Steenkamp and Fang 2011 for the relationship between market volatility and R&D spending). If they are successful, they can reshape the industry and generate new markets or value propositions (Ansari et al. 2016).

With respect to the effect of market volatility on radical versus incremental innovation in times of AI, we see the following research challenge.

Empirical evidence suggests that radical innovations may be more likely to succeed in volatile markets. For years, "green" cars like Tesla were in the market. During the Covid period, everything digital became increasingly popular. Investors realized that Tesla not only had an electric engine, but that Tesla's software was years ahead of its competitors. It was a digital car. The demand skyrocketed, and the firm was suddenly worth more than its important competitors combined. One may assume that a reason is that market volatility breaks inertia. For example, in the extreme case of Covid, working remotely was a necessity rather than a possibility. Future research could examine *why* consumers start to see radical innovations for what they are.

2.2 | Effects of AI on the Relationship Between Firm Culture and Type of Innovation

The two red arrows in Figure 1 describe how AI can alter existing relationships that have been taken for granted; in this case, AI will affect the relationship between firm culture and type of innovation. In times of AI, this relationship will consist of firm culture on AI and AI on type of innovation.

2.2.1 | Firm Culture on AI

Firms with a stronger innovation-centric culture are more likely to adopt AI in their innovation process early. This is because such firms focus on future markets, offer incentives for innovation, have a high tolerance for risk, and maintain internal markets (Tellis 2012). The focus on future markets (Chandy and Tellis 1998) aligns with serving the needs of future customers rather than current ones. Future customers stand to benefit from the superior products generated through better ideas facilitated by AI (e.g., Li et al. 2024). Incentives for innovation mean that managers who adopt AI early are rewarded for the resulting gains. High risk tolerance ensures that managers who implement AI are not penalized if AI does not meet every expectation or if some use cases do not succeed. Lastly, internal markets encourage managers to stay current and adopt new technologies, like AI, earlier than others to advance their careers and stay competitive. Since each manager in a firm with an innovation-centric culture has the incentive to adopt new technologies like AI early, the entire firm is likely to adopt AI earlier than competitors who have a less innovation-centric culture.

2.2.2 | AI on Type Innovation

There are two dimensions of how AI affects the relationship between firm culture and type of innovation: degree of automation (all human/hybrid/all AI) and degree of exploration (vs. degree of exploitation) (cf. March 1991). The degree of automation refers to the extent to which AI automates tasks, decisions, and processes that were previously manual. A high level of automation improves efficiency. The degree of exploration is the extent to which AI systems can experiment, engage in creative discovery, come up with new opportunities, and generate completely novel solutions.

A high degree of automation can have either a negative or a positive influence on the relationship between an innovation-centric culture and radical innovation. It is likely that the firm's inherent tendency for radical innovation is reduced if it increasingly focuses on important benefits of automation, like process optimization, to increase efficiency and to save costs. In contrast to an innovation-centric culture which encourages risk taking and focuses on future markets, automation processes typically use existing or even historical data and try to detect patterns in those. This increasing focus on the past may jeopardize the valuable focus on the future. As a consequence, a firm with a high degree of automation may be less likely to come up with radical innovations. However, the automation of processes can liberate time resources for employees. It depends on the company's culture what the managers do with those liberated time resources—increase efficiency by not hiring more people and laying them off—or letting employees use this time to focus on the development of radical innovations. In the latter case, the relationship of innovation-centric culture to radical innovation would be positive.

A high degree of exploration has a positive influence on the relationship between innovation-centric culture and radical innovation. The reason is that a high degree of exploration may help a firm to detect new solution spaces and new interrelationships of elements that humans may not have identified, for example due to cognitive fixation (Bayus 2013) or time limitations (Moreau and Dahl 2005). Human employees can then draw on a larger solution space when designing their radical innovations.

After analyzing the impact of AI on innovation at the company level, we now focus on the stages of the innovation process outlined in Section 3.

3 | Ideation in the Innovation Process

While the theoretical model in Section 2 analyzes differences *across* firms with respect to innovation, Section 3 of this article focuses on the innovation process *within* firms in times of AI.

Figure 2 shows the innovation process within firms (cf. Hauser et al. 2006). Ideation is a key point of leverage in the firm's innovation strategy (Dahan and Hauser 2002a, 2002b). Ideation consists of (a) the identification and analysis of technological developments, market trends, and Voice of the Customer, (b) idea generation, (c) idea screening and idea selection, and (d) idea refinement. In the ideation stages, the nature of work is experimental, often chaotic. In later stages of the innovation process,

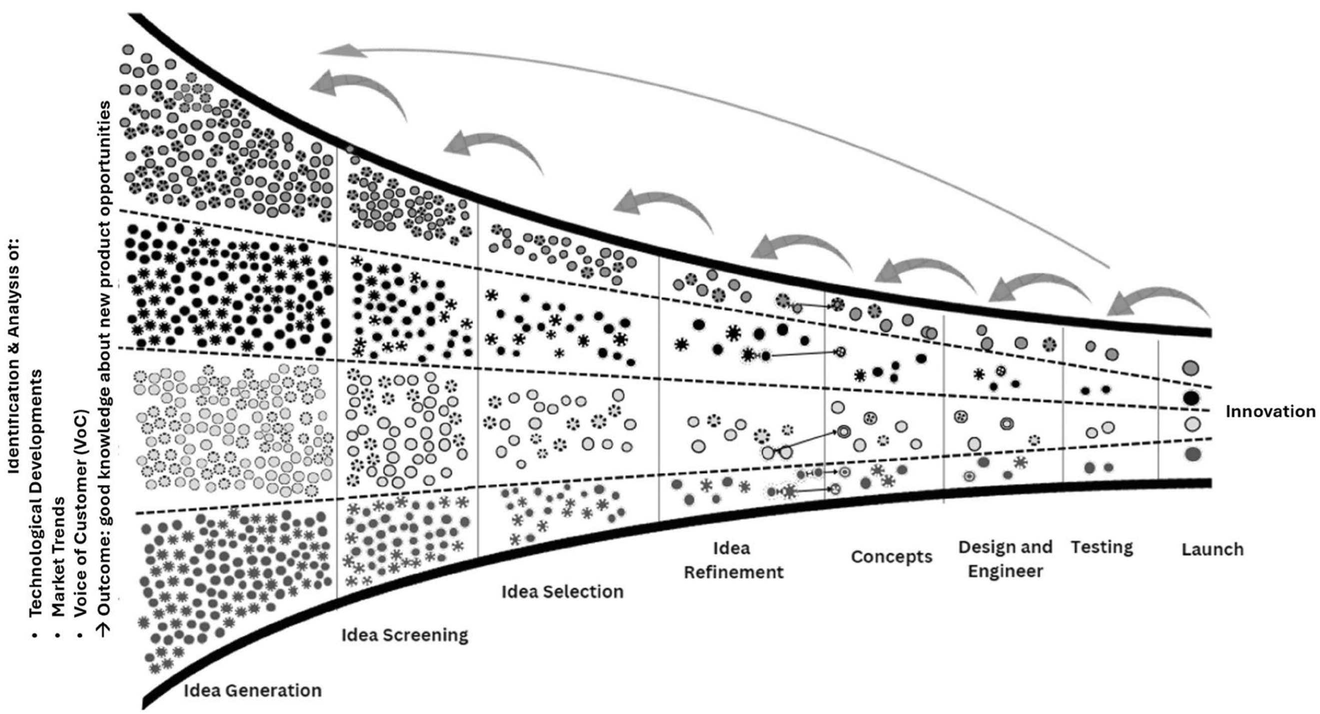

FIGURE 2 | Framework of the innovation process (*Source:* Adapted from Hauser et al. 2006).

the nature of work becomes more structured, disciplined, and goal-oriented. In the ideation stages, the commercialization date is unpredictable, the funding variable, and revenue expectations are often uncertain, sometimes speculative. In the later stages of the innovation process, the commercialization date is definable, the funding budgeted, and the revenue expectations are believable with increasing certainty. Overall, ideation is the beginning of the innovation process, when risk remains high and the output uncertain. Why do we adapt the framework? What are the main changes?

To answer these questions, we start with the framework of Hauser, Tellis, and Griffin (2006, 701), which consists of the stages of idea generation, concepts, design and engineering, testing, and launch. Supporting Information Appendix B shows an image of the innovation process of Hauser et al. (2006). The latter four stages in our new framework are identical to those in Hauser et al. (2006). We do not elaborate on the use of AI in these steps of the innovation process, as Cooper (2024) provides an excellent review. Research has made much progress since this framework's original publication in 2006. A substantial portion of the progress is due to AI. Notably, AI has the ability to automate (Davenport 2018) and substantially speed up (Verganti et al. 2020) processes. Note that some of the additional stages were mentioned in the context of a reduction in cycle times (see Koen et al. 2001; Smith and Reinertsen 1992, 1998).

Next, we will contrast the situation in the times of Hauser et al. (2006) and the developments that happened since that led us to include the respective stages in the innovation process.

3.1 | Identification and Analysis of Technology, Markets, Customers

Managers in the times of Hauser et al. (2006) had access to approaches like netnography of online communities (Kozinets 2002) or lead user detection (von Hippel et al. 2006); yet such analyses were mostly ad-hoc and not automated. So, managers often relied on traditional market research. Today, managers have access to recent developments in market research (Arora et al. 2025), in technology (e.g., by detecting weak signals from patents that represent emerging technologies), markets (Matthe et al. 2023), or voice of the customer (for a review see Hauser et al. 2023) due to AI. Pioneering studies were Netzer et al. (2012) and Tirunillai and Tellis (2014). Thus, managers may have much better information to identify promising new product opportunities than two decades ago. The output of this stage, better information, allows managers to precisely define the search space for new products.

3.2 | Idea Generation

While this is the only stage in ideation that was already present in Hauser et al.'s (2006) innovation process, there have been massive advancements. While two decades ago approaches like six-hats (De Bono 1995), templates (Goldenberg et al. 1999, 2001), and the theory of inventive problem solving (Altschuler 1985) were state of the art, nowadays, ideas generated by LLMs outperform ideas generated by humans. The number of generated ideas, that is, the output of this stage, skyrockets.

3.3 | Idea Screening

Experts can reliably judge the quality of ideas. Experts possess tacit knowledge about customers, products, and markets, as well as experience, intuition, and the ability of sensemaking (Verganti et al. 2020; also see Sukhov et al. 2021). However, knowledgeable and experienced experts are scarce in most sectors. At the same time, selecting and developing mediocre ideas can be costly. Since AI boosts productivity, an increasing number of ideas decreases the time experts can dedicate to fully understand each idea because of limited cognitive capability (Bell et al. 2024) or attention span. Thus, a productivity increase in idea generation may increase the probability of selecting an inferior idea. To address this issue, our framework differentiates between idea screening and idea selection to reduce the number of ideas.

While two decades ago, managers directly selected the best ideas out of those that were generated, the sheer number of ideas made an immediate selection impractical. Thus, the critical task moves from idea generation to idea screening (Girotra et al. 2023). In idea screening, AI approaches separate the good from the bad ideas. New AI approaches like Word Atypicality (Bell et al. 2024) assist in performing this task. So, the output of this stage is a set of good ideas.

3.4 | Idea Selection

Once the good ideas have been separated from the bad, managers need to select the best ideas. Because the bad ideas were already screened out, they can dedicate more time to each of the remaining ideas to make a well-thought decision. The best ideas are the output of this stage. While AI does a good job in idea screening, to date it still has a hard time selecting the best ideas (Bell et al. 2024). So as of today, human experts usually select the best ideas manually. Moreover, human idea selection also assists with taking on responsibility and commitment for the future development of ideas. AI will assist humans in selecting the best ideas in the future. An early study to select ideas is Wei et al. (2022) who construct similarity networks of crowdfunding projects to predict funding outcomes.

3.5 | Idea Refinement

While the quality of a raw idea is a predictor for ultimate success (Kornish and Ulrich 2014), one needs to develop and refine the ideas to allow them to reach their full potential (Koen et al. 2001). Fully developed ideas that can be developed into concepts are the output of this stage.

Overall, by adjusting a widely accepted framework to recent developments in AI, in the subsequent sections we outline research opportunities, some of which do not exist a few years ago. We also set research priorities to guide researchers in the years to come.

3.6 | Research Challenges

- Determine which types of data need to be measured and collected and which metrics are helpful to guide the transition from idea to launch across the entire innovation process (cf. Sozuer et al. 2020; Wang et al. 2021).
- Modern product management relies on tools like the Business Model Canvas or Agile product development (Shulman et al. 2023). Researchers should
  - Develop integrated tools that help to manage the entire innovation process.
  - Determine in which stages of the ideation process managers can save time due to AI and in which stages managers should use the saved time for additional iterations to improve the quality of the output and to decrease risks.

4 | Identification and Analysis of Technological Developments, Market Trends, and Voice of the Customer to Gain Knowledge of New Product Opportunities

> The value of an idea lies in the using of it. *Thomas Alva Edison*

The innovation process starts with the identification of a problem or need, that is, with a technological or market opportunity that provides value to actual or potential customers and that the firm wants to pursue. The firm's goals typically drive this step (Koen et al. 2001). Next, the firms analyze these technological or market opportunities. They need to make early technology or market assessments, which are often subject to high uncertainty (Beliveau et al. 2002). Thereby, firms make extensive use of voice of the customer (Hauser et al. 2023) and of competitive intelligence, trend analyses (Koen et al. 2001). Opportunity identification and analyses stimulate R&D activities designed to create an innovation to solve the respective problem/need (Rogers 2003). If early on a firm can identify a set of unmet customer needs, the best business opportunity, or a technological innovation, then the remaining steps become implementation (Hauser et al. 2006). Table 1 provides an overview of AI-related research regarding identification and analysis of new product opportunities. Thereby, we first present research that identifies consumer behavior and consumer needs, and then research that is related to the market dimension.

Whether new products are worth a firm's investment is determined by consumers' purchase decisions. If firms manage to reliably identify customers' preferences, they can develop innovative products that meet those preferences. Since consumer behavior decides whether a product innovation becomes a success or a failure, one would typically start such a review by focusing on relevant consumer-related constructs—both on the individual level (Proserpio et al. 2020) and on the cultural level (Hauser et al. 2006). However, there is a recent high-quality review at the intersection between these topics and AI (Kopalle et al. 2022), so we refer to this important publication for readers who are interested in those topics.

Instead, we focus on the methods firms can use to identify relevant consumer preferences from online data. In the past, firms relied on interviews, focus groups, or surveys to identify customer needs (Hauser et al. 2023). Nowadays, consumers leave behind vast amounts of traces every day (Liu et al. 2016; Shulman et al. 2023). These traces can contain important ideas for innovations. Many AI technologies collect, store, and process these traces (Bradlow et al. 2017). Examples include consumers' digital footprints across devices, online and offline (Kopalle et al. 2022). The usefulness of AI often critically relies on a firm's ability to collect this abundance of individual-level data (Bleier et al. 2020). After obtaining the data, firms can then use AI for automated analyses (Huang and Rust 2018) to identify opportunities for innovations.

AI provides the opportunity to generate important insights in an automated way (Lee and Bradlow 2011). Building on earlier research on how to transform user generated content in text form into information that firms can make use of (Archak et al. 2011; also see Berger and Packard 2022, 2023), Timoshenko and Hauser (2019) identify customer needs from vast amounts of user generated content using AI. They also show that user generated content is at least as valuable as a source of customer needs compared with traditional methods. Dhillon and Aral (2021, also see Aral and Dhillon 2023) decompose users' content consumption journeys into user and content factors to model consumers' dynamic interests. Dzyabura and Hauser (2011, 2019) develop approaches in which consumers learn about their own preference weights. Firms can use this knowledge. Besides text, images can also provide very relevant information. Some promising approaches are currently being developed for images (Dzyabura et al. 2023; Haase et al. 2023; Pavlov and Mizik 2023; Sisodia et al. 2022; Tetzlaff et al. 2023; Zhang and Luo 2023; Zhang and Shankar 2022) and video (Lu et al. 2016; Jiang et al. 2022), but according to our awareness, they have not been explicitly used to mine consumers' preferences. For an excellent in-depth review on AI in voice of the customer, please see Hauser et al. (2023). This review goes much beyond new product opportunity identification and analysis.

Researchers also use machine learning to provide insights about competitive intelligence. Netzer et al. (2012) and Tirunillai and Tellis (2014) are the pioneers of transforming publicly available data into perceptual, respectively, positional maps. Years later, Matthe et al. (2023) develop a more sophisticated tool.

4.1 | Potential Generalizations

- There is high-quality research that deals with the analyses of text and images, but analyses of video, for example based on TikTok, and voice are underrepresented in marketing literature.

4.2 | Research Challenges

- The perennial paradox in innovation is the tension between focusing on constant incremental innovations

TABLE 1 | Research regarding identification and analysis of new product opportunities.

		Article	Summary	Major findings
Information about consumers and their preferences	Text	Dhillon and Aral (2021) *Marketing Science*	Use of unstructured, dynamic, high-dimensional data to extract valuable insights regarding consumers' dynamic news consumption patterns	Approach can summarize each user's content consumption journey across content attributes
	Images	Dzyabura et al. (2023) *Marketing Science*	Demonstrate that machine-learning methods applied to product images enhance predictive ability relative to benchmarks	Derive optimal policy for launch decisions that takes prediction uncertainty into account; up to 40% profit improvement
	Text	Dzyabura and Hauser (2011) *Marketing Science*	Develop a new approach to extract consumers' heuristic decision rules	Adaptive questions by this algorithm outperform market-based questions when estimating heuristic decision rules
	Text	Dzyabura and Hauser (2019) *Marketing Science*	Capture consumers' preference-weight learning over attributes during online search processes	Demonstrate that existing search-theory solutions may not be optimal when preference weights are learned
	Text	Li et al. (2024) *Marketing Science*	Exploration of the potential of large language models to substitute for human participants in market research: Development of a new method to generate perceptual maps.	The proposed new method generates outputs that closely match those generated from human surveys: agreement rates between human- and LLM-generated data sets reach over 75%. This new method of fully or partially automated market research will increase the efficiency of market research by meaningfully speeding up the process and potentially reducing the cost
	Image	Liu et al. (2020) *Marketing Science*	Recognize that images are close to surpassing text as the medium of choice for online conversations. Develop a method for visual listening in	Find a strong link between brand portrayal in consumer-created images and consumer brand perceptions collected through traditional methods
	Video	Lu et al. (2016) *Marketing Science*	Develop a video-based automated recommender system using real-time in-store videos that can improve the experiences of garment shoppers	New approach consistently outperforms self-explicated conjoint and self-evaluation after try-on
	Text	Timoshenko and Hauser 2019 *Marketing Science*	Develop a new approach that identifies customer needs from user generated content	Show that user generated content is at least as valuable as source of customer needs than conventional methods
	Text	Wang et al. (2022) *Journal of Marketing*	Develop an approach to gain insights into how consumers combine a product's technical specifications to form abstract product benefits?	Development of a framework that guides managers to monitor only portions of review content that are relevant to specific attributes of interest

(Continues)

TABLE 1 Continued

		Article	Summary	Major findings
Information about market/ competition	Text	Matthe et al. (2023) *Marketing Science*	Develop a novel dynamic mapping framework that identifies firms' trajectories from high-frequency and potentially noisy data	EvoMap, a tool to study the trajectories of publicly listed firms
	Text	Netzer et al. (2012) *Marketing Science*	Build a novel approach to convert user-generated content to market structures and competitive landscape insights	Generation of perceptual maps; high correlation between this novel approach and findings based on data collection methods
	Text	Tirunillai and Tellis (2014) *Marketing Science*	Build a novel approach to extract key latent dimensions of consumer satisfaction with quality ascertaining the valence, labels, validity, importance, dynamics, heterogeneity of these dimensions	generation of dynamic positioning maps; high correlation between new approach and scores of consumer reports; introduce LDA in marketing literature
	Image	Zhang and Luo (2023) *Marketing Science*	Investigate whether consumer-posted photos can serve as indicator of restaurant survival beyond reviews, firm characteristics, competitive landscape, and macroconditions	Consumer-posted photos are a strong predictor of restaurant survival. Informativeness of photos (proportion of food photos) more important than photographic attributes

without being blinded to the arrival of radical innovations. AI is typically trained using historical data that reflect past and current consumer preferences. Yet, Ford once said: "If I had asked people what they wanted, they would have said faster horses." So, researchers could dig into whether and what type of consumer and market data managers can use to identify opportunities for radical innovation.

- Likewise, radical innovation often arises from technological advances combined with entrepreneurial vision. For instance, although German scientists developed the MP3 format in the 1980s and 90s, it gained significant traction through Napster around 2000 and achieved commercial success when Steve Jobs incorporated it into the Apple iPod. Managers should therefore remain alert to emerging technologies that could meet customer needs (Di Stefano et al. 2012). However, while AI research addresses the Voice of the Customer and Market Developments (Table 1), managers and scientists would benefit from more studies on technology development, screening, and aligning technology with consumer preferences. Using AI to identify new technologies based on news or patent data provides insights into recent technological inventions (see Mühlroth et al. 2023 for a non-marketing approach).

5 | Idea Generation

Idea generation is the birth, development, and maturation of the business or technological opportunity into concrete ideas (Koen et al. 2001).

Idea generation is critical to the success of new products and to marketing strategy (Girotra et al. 2010; Luo and Toubia 2015; Toubia 2006; Toubia and Florès 2007). Ultimately, firms are interested in having a few outstanding ideas, that is, firms search for the extreme end of the idea quality scale. The probability for firms to obtain outstanding ideas in the ideation stage increases with (a) more ideas rather than few ideas, (b) a higher rather than a lower mean idea quality, and (c) a higher rather than a lower variance in idea quality (Terwiesch and Ulrich 2009).

In recent years, research focuses on ideation contests or communities like Dell's Ideastorm, as ideas submitted by users tend to be slightly better than ideas submitted by experts (Poetz and Schreier 2012; also see Schreier et al. 2012). Much relevant research on idea generation is on how to get the contest right for the people, that is, a contest perspective (e.g., Girotra et al. 2010; Wooten and Ulrich 2017), or how to get the best people for the contest, that is, an ideator perspective (Bayus 2013; Franke et al. 2014; Huang et al. 2014).

In the past three years, LLMs have received a lot of attention because they surpassed all expectations across a wide variety of tasks. In fact, in the development of simpler content like product reviews, the output from LLMs is indistinguishable from content written by human experts (Carlson et al. 2023; also see Reisenbichler et al. 2022 for a similar finding of natural language generation on landing pages as well as Schweidel

TABLE 2 | Overview of AI-related literature regarding idea generation.

Article	Summary	Major findings
Boussioux et al. (2023) *Organization Science*	Comparison of AI and human crowdsourcing in generating solutions for a complex opportunity in the sustainable circular economy	– Solutions from GPT-4 and humans are of similar quality—Humans provide more novel solutions—GPT-4 provides higher value solutions
Li et al. (2024) *Working Paper*	Investigation of the creative potential of AI-generated ideas vs. ideas generated by human laypeople and creative experts	– GPT-4 generated ideas are more original and innovative than ideas generated by laypeople and creative professionals—GPT-4 outperforms humans in creative form (language used) and creative substance (idea is more novel)—Rewriting human ideas using GPT-4 improves creativity due to improvement in creative form
Demir et al. (2024) *ECIS*	Test whether AI support improves the creativity of human ideators	Humans collaborating with AI – produce more ideas – produce ideas with more details – produce ideas that fall into more categories – produce fewer original ideas than humans working independently; this means that access to AI increases average creativity, but decreases the likelihood of outstanding work
Dew et al. (2022) *Marketing Science*	Exploration of data-driven perspectives at the interplay between logo design and brand identity creation	– Model supports managers by suggesting typical logo features for a brand – Model predicts consumers' reactions to new brands or rebranding efforts
Doshi and Hauser (2024) *Science Advances*	Study of the causal impact of AI-generated ideas on the production of short stories in an online experiment, where some writers obtained story ideas from an LLM	– Access to AI ideas causes stories to be evaluated as more creative, better written, and more enjoyable, especially among less creative writers – Results point to an increase in individual creativity at the risk of losing collective novelty
Eisenreich et al. (2024) *Technovation*	Examination of the comparative effectiveness of AI-generated ideas and traditional expert workshops	– Ideas generated with GPT-4 not only match but can outperform ideas generated by expert sessions in terms of novelty – Increased novelty comes with a cost of decreased feasibility → critical balance – AI-based stimulation may limit the creativity and motivation of experts
Girotra et al. (2023) *Working Paper*	Comparison of ideas from Wharton's MBA students vs. GPT-4 for a cheap incremental innovation	– GPT-4 generated ideas are faster, better, and cheaper – Critical task moves from idea generation to idea screening
Guzik et al. (2023) *Journal of Creativity*	Investigation of the creative abilities of GPT-4 using the Torrance Test comparing it to humans	– GPT-4 scored within the top 1% for originality and fluency – GPT-4 has high scores for flexibility
Haase and Hanel (2023) *Journal of Creativity*	Comparison of ideas generated by humans with ideas generated by AI (alternative use test)	– No qualitative difference between AI and human-generated creativity – 9.4% of humans more creative than the most creative AI, GPT-4

(Continues)

Article	Summary	Major findings
Hubert et al. (2024) *Nature: Scientific Reports*	Assessment of the creative potential of humans compared with AI using divergent thinking tasks	– AI more creative than humans – AI more original and elaborate
Joosten et al. (2024) *IEEE Engineering Management Review*	Comparison of ideas from professionals vs. AI for new sustainable packaging solutions that add value for the customer	– AI-generated ideas score significantly higher in novelty and customer benefit – Feasibility scores are similar – AI achieves majority of top-performing ideas
Koivisto and Grassini (2023) *Nature: Scientific Reports*	Comparison between humans and AI chatbots regarding divergent thinking	– AI chatbots outperform humans on average – Human responses included poor-quality ideas – Best humans still outperform AI chatbots
Meincke et al. (2024) *Working Paper*	Investigation of methods to increase the dispersion in AI-generated ideas: development of a new product for college students priced under 50 USD.	– Pool of ideas generated by GPT-4 less diverse than pool of ideas generated by humans – Diversity of AI generated ideas can be increased by prompt engineering – Chain-of-Thought prompting leads to the highest diversity of ideas; also generated the highest number of unique ideas of all prompts
Mukherjee (2024) *Working Paper*	Comparison of AI-generated project titles for hypothetical crowdfunding campaigns with field data	– AI generates unique content even under increasing task complexity – AI-generated titles have face validity – AI-generated titles that diverge from field data
Urban et al. (2024) *Computers & Education*	Comparison of university students on complex problem-solving performance with and without the use of AI	– The use of AI increases students' self-efficacy for task resolution, enhanced the quality, elaboration, and originality of solutions – Students who use AI perceive tasks to be easier and to require less mental effort
Zhou and Lee (2024) *PNAS Nexus*	Study a dataset of over 4 Mio artworks from over 50,000 unique users. Examination of the effects of AI on creative productivity	– Human's creative productivity increased by 25% since the widespread use of AI – Peak artwork content novelty increases over time – Average content novelty decreases over time

et al. 2024). How do they perform in creative tasks like idea generation? Initial studies already provide conflicting evidence. Table 2 provides an overview of studies in which AI helps to generate ideas and designs. Girotra et al. (2023) analyze an idea contest in which participants suggest ideas for inexpensive new products that firms can soon introduce into the market. They compare ideas submitted by Wharton's MBA students with ideas submitted by GPT-4. GPT-4 wins on every dimension. The average purchase probability is 49% (with examples) and 47% (without examples) compared with only 40% for human ideators. Out of the 40 best ideas, GPT-4 developed 35. Moreover, GPT-4 managed to generate the ideas in hours, where it took humans days to generate the same number of ideas. Girotra and colleagues conclude that GPT-4 is faster, better, and cheaper than human ideators! In a study on divergent thinking, which also relates to creativity, Koivisto and Grassini (2023) also find that AI generates better results on average, but that the best humans still outperform AI. Li et al. (2024) show that GPT-4 generated ideas are more original and innovative than ideas generated by humans. Searching for solutions for a complex problem from the circular economy, that is, a more radical innovation, Boussioux et al. (2023) compare solutions from human expert solvers with solutions generated by GPT-4. They find that humans generate more novel solutions, but GPT-4 generates higher value solutions. The conclusion would be that the focus switches from idea generation to idea evaluation.

Beyond ChatGPT, when it comes to designs, Dew et al. (2022) develop a novel logo feature extraction algorithm that decomposes pixel-level image data into meaningful features. This approach is interesting because designers can use the output as stimuli for ideation.

5.1 | Case Studies

Marketing literature calls for an empirics first approach; this approach can reveal novel research questions untethered to theory (Golder et al. 2023). Taking a look at empirics is particularly relevant to a rapidly-moving field like AI. To contrast how the scientific literature and industry differ from each other in idea generation, we now present two exemplary case studies from different industries: the food industry (Manitoba Harvest) and the pharmaceutical industry (Roche).

5.1.1 | Case Study Idea Generation in the Food Industry (cf. Cooper 2024)

> Manitoba Harvest (MH), a producer of healthy hemp-based foods, has launched a breakthrough product Bioactive Fiber, "discovered" with AI. MH partnered with Brightseed, a bioactives firm. Brightseed's AI platform, Forager, identifies naturally occurring molecules in plants and microbes (bioactives) and links them to specific human health benefits, thereby accelerating food discovery and validation and cutting the development time from years to months. The AI platform has identified 40 times more bioactive plant compounds than what had previously been documented.

5.1.2 | Case Study Roche: Solution Space Exploration in the Pharmaceutical Industry (cf. Roche 2022)

> The traditional drug development process is linear and sequential, says Casper Hoogenraad, Vice President and Head of Neuroscience in Genentech's Research and Early Development (gRED) organization. "Researchers start with a single target that, based on disease biology or human genetics, is dysregulated and then figure out what kind of therapeutic might modulate the activity of that target be it a small molecule, an RNA approach, or a large molecule, like an antibody." Advancing AI tools, such as ML, in drug discovery and healthcare, is more important than ever as drug developers are moving beyond the universe of familiar targets and are tackling increasingly challenging ones to treat more complex diseases with high unmet need. Scientists are using these tools to mine data for insights that are unreachable with traditional methods, at a scale and speed that were previously unattainable. [...].

> Unlike the conventional approach, which starts with known targets, the partnership will generate and analyze different types of cellular and genetic data—at a huge scale—to build unprecedented maps of human cellular biology. These maps can be leveraged to identify novel biological relationships and ultimately help discover new targets to bring better medicines to patients, and faster. "We're layering a lot of datasets, including high-resolution imaging of how cells respond to genetic changes and chemical perturbations, or disturbances, along with data on how small molecules affect those responses—and using AI to analyze it all," says Bonni (Senior Vice President and Global Head of Neuroscience and Rare Diseases, Roche Pharma and Early Development).

5.2 | Comparison Between Scientific Literature and Case Studies From Industry

Table 3 shows an overview of the results from literature versus case studies from the industry.

5.3 | Potential Generalizations

5.3.1 | Generalizations From Literature

- AI increases the volume of ideas generated and the speed of ideas generated (Demir et al. 2024; Girotra et al. 2023; Zhou and Lee 2024)
- AI-generated ideas rate higher with respect to different dimensions of creativity (Li et al. 2024; Girotra et al. 2023; Guzik et al. 2023; Hubert et al. 2024; Urban et al. 2024)
- AI-generated ideas perform particularly well for dimensions that relate to incremental rather than radical innovations (higher value rather than novelty; Boussioux et al. 2023; Girotra et al. 2023; Meincke et al. 2024)

5.3.2 | Generalizations From Case Studies

- While marketing literature predominantly studies hybrid ideation, companies prioritize data-driven ideation based on complex data structures.
- Companies engage in exploratory ideation (one example is Huang et al. 2024)

5.4 | Research Challenges

Table 4 provides an overview of research challenges in idea generation.

6 | Idea Screening and Idea Selection

6.1 | Idea Screening

In idea screening, firms aim to separate good from bad ideas. The goal is to substantially reduce the number of ideas, that is, to screen the bad ideas while maintaining the good ideas (Bell et al. 2024; Hammedi et al. 2011).

Since consumers participate in idea generation (Dahl et al. 2015), the number of ideas increases substantially. We expect the number of ideas to skyrocket even further in the

TABLE 3 | Overview of AI-related literature regarding the generation of ideas and designs.

		Scientific literature (marketing and related disciplines)	Case studies from industry
Approach	Starting point	Precise research question, then focused on analyzing the research question (s)	Precise target definition, then exploratory
	Main task	Generation and analysis of data	Exploration of vast amounts of internal data
	Data source	One or few	Cross-disciplinary results by integration of multiple data sources that form complex data structures
	Dimensions	One or few	Multi-dimensional, identification of patterns/connections humans may miss
	Scalability	Limited	High
	Type of search	Sequential	Parallel
Results	Solution spaces	Limited	Broad
	Diversity of ideas	Reduction with potential mitigation through prompting techniques	Increased diversity potential leads to new radical innovations
	Enhancement of human creativity	Mixed—AI can support or limit human creativity	Enabler—AI provides results, humans define target and make final decisions

near future because AI can generate ideas at a much faster rate than human ideators (Girotra et al. 2023). In fact, researchers see the risk of an "evaluation overload," that is, of an incoming flood of ideas that are lost because firms have no efficient way to evaluate them properly (Eapen et al. 2023). Therefore, the bottleneck, in the early phases of the innovation process in organizations, shifts from generating ideas to screening ideas (Girotra et al. 2023).

Traditionally, the responsible managers have the daunting task of screening these ideas (Toubia and Florès 2007). In some settings, they can receive assistance from users, consumers, or Amazon Mechanical Turk workers to evaluate the ideas (Cao et al. 2024; Toubia and Florès 2007). But the use of human judges has shortcomings. Some evaluators may act strategically, for example, if their own ideas are competing with the focal idea. There may be social processes that affect the outcome, like strategic evaluation, a hierarchy of authority, or a lack of hierarchy (Keum and See 2017) that may affect the outcome. Amazon Mechanical Turk workers may not have the required expertise to evaluate each idea properly. The more "cutting edge" a product is, the more likely experts are required (O'Quin and Besemer 1999). Yet, there may not be enough judges with in-depth knowledge to evaluate each idea (Toubia 2006). When evaluating (too) many ideas, the judges may get tired or lose focus. So, AI-based screening algorithms are particularly useful to reduce the total number of ideas to a manageable number. A first step away from the traditional expert approach in idea screening stems from Toubia and Florès (2007). Toubia and Florès were the first ones to develop a more sophisticated approach to let customers participate in idea screening. Thereby, they partially automatized the idea-screening process.

The next step is the use of AI in idea screening. Table 5 provides an overview of the increasing studies that use AI to screen ideas. Hoornaert et al. (2017) take it one step further and apply machine learning. Moreover, they identify key indicators of good ideas in ongoing communities: content, contributor, and crowd feedback. They use these insights to develop an approach managers can use to screen ideas in real time. Bell et al. (2024) develop an idea-screening approach that relies on theory about the origins of superior creative performance (Berger and Packard 2018; Stephen et al. 2016; Toubia and Netzer 2017). Bell et al. (2024) extend those established theories and apply them to idea screening. They develop the Idea Screening Efficiency Curve, which is a tool that allows managers to choose a benchmark and compare this benchmark to the model performance. They manage to screen 44% of all ideas at the cost of only losing 14% of the good ideas. While Bell et al. (2024) and Just, Hutter, et al. (2024) use theory-based AI to screen ideas, Lane et al. (2024) study how evaluators react to AI recommendations with and without explanations.

Rupp and Füller (2024) and Rupp et al. (2023) use affective computing, that is, they explore the predictive power of AI-measured spontaneous effect on idea evaluation.

6.2 | Idea Selection

In most businesses, there are so many product and process ideas that *the critical activity* is to choose which ideas to pursue to achieve the most business value (Koen et al. 2001).

After the ideas have been screened and reduced to an amount that is handy for evaluators, managers select those ideas for further development that will have a substantial chance at success (Hammedi et al. 2011). The goal is that only the most promising ideas survive (Terwiesch and Ulrich 2009) because the selection of a good raw idea leads to a greater level of success (Kornish

TABLE 4 | Overview of research challenges in idea generation.

Inspiration	Idea	Research challenge	Data needed to address challenge	How to acquire data
Literature	Assessing the Impact of AI on the Diversity of Idea Pools—Alleviating the Tension between Incremental and Radical Innovation	One risk is that the use of AI seems to narrow the number of perspectives in a pool of new ideas, perhaps because they may favor mainstream or historically successful ideas. This can be problematic, because good ideas may be very novel and/or originate at the margins of solution spaces or come from other disciplines. For example, the invention of the marine chronometer by John Harrison, a self-taught clock maker, in the 18th century, solved the problem of the determination of longitude at sea. On an aggregated level, i.e., on the level of the idea pool, there is evidence that AI can have positive or negative effects on the diversity of ideas (positive: Demir et al. 2024 on number of categories; negative: Doshi and Hauser 2024; Meincke et al. 2024). Future research could analyze across a number of different tasks, for example incremental vs. radical innovation, or more vs. less complex products, or under which circumstances the diversity of an idea pool increases or decreases with and without the use of AI	• Metrics on diversity in idea pools: number of categories, number of unique ideas (with similar ideas being grouped), breadth of ideas on a topic, semantic distance between ideas, divergence from prior similar idea pools • Scores on how ideas differ: complexity, novelty, uniqueness, originality, market value, feasibility • Background information on ideators • Logs on how users interact with AI	• Ideation experiments: ideation sessions in which an AI-only idea pool is compared with human only idea pools and different types of AI-human-hybrid approaches; participants have to be randomized across the approaches that include humans • Secondary analyses on existing ideation contests and/or communities before and after the introduction of AI • Industry data that incudes before/after AI introduction
	Leveraging AI for Real-Time Feedback to Counter Cognitive Fixation and Expand Solution Spaces	In the beginning of the innovation process, a diverse idea pool is important, as having more perspective increases the probability of having at least one outstanding idea (Terwiesch and Ulrich 2009). Cognitive fixation of ideators, i.e., ideators' tendency to become increasingly incremental in creative processes (Bayus 2013), can hinder the development of a diverse pool of ideas. One reason for this is that human ideators typically look for new ideas in known solution spaces. AI could recognize patterns of incremental thinking and provide ideators with real time feedback using new topics, cross-disciplinary perspective, or novel facts. This can lead ideators to explore unfamiliar solution spaces which increases the probability of balancing familiarity with novelty (Toubia and Netzer 2017), i.e., coming up with radical innovations	• Metrics that measure fixation or incrementality: novelty, semantic distance • Logs on how users interact with AI • Background information on ideators	• Ideation experiments: ideation sessions in which an AI-only idea pool is compared with human only idea pools and different types of AI-human-hybrid approaches; participants have to be randomized across the approaches that include humans

(Continues)

TABLE 4 Continued

Inspiration	Idea	Research challenge	Data needed to address challenge	How to acquire data
	Tailoring Prompting Techniques to Boost Creativity across Innovation Types	Recent findings show that effective prompting can significantly enhance idea quality and diversity. Meincke et al. (2024) show that the typical reduction in diversity in AI-generated ideas can be mitigated by adequate prompting techniques like Chain-of-Thought (CoT) Prompting, i.e., by guiding a model to generate responses step-by-step, breaking down its reasoning process to produce more coherent and logically structured output. While CoT is very promising, it is unlikely that one prompting technique excels in all innovation tasks, from incremental (Girotra et al. 2023; Meincke et al. 2024) to radical. Research would benefit from a deeper understanding of how different prompt architectures (Brucks and Toubia 2025) and prompting techniques affect results across a number of different tasks and evaluation dimensions. Exploring the interplay between prompting techniques and innovation types for different products could unlock new potentials in AI-assisted creativity. This research could develop customized AI strategies for different tasks	• Human-generated ideas as control group • Different tasks related to incremental innovations vs. radical innovations and cultural vs. functional innovations • Evaluation metrics: complexity, novelty, uniqueness, originality, market value, feasibility • Background information on ideators • Logs on how users interact with AI	• Ideation experiments in which participants have to be randomized across scenarios
	Preserving and Enhancing the Creativity of Human Top Ideators	The effect of AI on the top ideas can either be positive or negative compared with humans (positive: Guzik et al. 2023; Joosten et al. 2024; negative: Chakrabarty et al. 2024; Demir et al. 2024; Doshi and Hauser 2024; Haase and Hanel 2023; Koivisto and Grassini 2023). This dichotomy highlights that solely relying on AI for innovation can be problematic. Human ideators can be highly creative and impactful and they can make the difference (Griffin et al. 2012; Schilling 2018). Think of Marie Curie, Thomas Alva Edison, Steve Jobs, Elon Musk, or Nikola Tesla. As a consequence, human creativity should be preserved and enhanced. For example, the creative process of human ideators consists of 4-stages (Guilford 1968): preparation, incubation, illumination, and verification. It would be interesting to determine at which stage the use of AI is the strongest on average vs. outstanding innovators	• Idea generation outputs for human and AI-generated ideas • Evaluation metrics: complexity, novelty, uniqueness, originality, market value, feasibility • AI model data (prompting techniques) and human data (participant background—expertise, experience, personality)	• Ideation experiments in which participants have to be randomized across scenarios

(Continues)

TABLE 4 Continued

Inspiration	Idea	Research challenge	Data needed to address challenge	How to acquire data
Industry	Impact of AI Search Strategies on Innovation: Digging Deep vs. Going Broad	An important question for human ideators is whether depth or breadth of knowledge allows to come up with better ideas (Custodio et al. 2019; Pescher et al. 2025; Teodoridis et al. 2019). But humans are subject to cognitive limitations, whereas AI is less so. Therefore, this result may or may not be transferable to AI. So, the question is whether AI's main benefit is that it allows to expand exploration across different data sources and topics to previously unchartered territory or whether digging deeper can lead to superior ideas. The answer to this question may differ between dimensions, e.g., incremental vs. radical innovations, more vs. less complex innovations, or it may differ between product types	• Access to different large databases that can be combined; exploratory: thus, the precise characteristics are unclear • Some classification of the types of innovation, i.e., incremental vs. radical • Pattern classification data on patterns generated by AI, e.g., relationship strengths between variables • Outcome variables: market performance, consumer reaction toward the innovations	• Industry cooperations to obtain data • Scraping the web to obtain additional variables • Use of advanced AI models (e.g., neural networks) to detect non-obvious patterns • Development of a pattern classification system, e.g., based on relevance, relationships • Use predictive studies to assess the generalizability of patterns
	AI's ability to Identify Non-Obvious Relationships	Based on the case studies on important benefit of AI is to discover patterns in complex data structures that humans may miss. This is a new research area in marketing and innovation and mainly exploratory. Can such patterns of non-obvious relationships between variables be classified? Are some patterns more promising than others, somewhat in analogy with Goldenberg et al.'s (1999, 2001) famous templates? This type of research would be more closely related with computer science.		

and Ulrich 2014). This way, the firm can focus its limited resources on the ideas with the highest market potential (Toubia and Florès 2007).

Traditionally, scholars considered idea screening and idea selection to be the same process. Yet, in times of an increasing number of ideas, idea screening and idea selection have developed into different topics. The reason is that the consequences of erroneous decisions differ between screening and selection. In idea screening, the risk is to screen some good ideas that are then not pursued. Screening good ideas does not have high direct costs associated with it but has opportunity costs in the form of sales that do not materialize. In contrast, selecting the "wrong" idea can lead not only to high opportunity costs but to a product flop after a long and expensive product development process. Thus, managers typically put a much stronger emphasis on idea selection than on idea screening. In idea screening, not all ideas may receive in-depth scrutiny. In idea selection, all ideas receive close attention.

In idea selection, humans are typically heavily involved (Kornish and Ulrich 2014), because they may possess tacit knowledge (von Hippel and Von Krogh 2016) useful in idea selection. Such tacit knowledge may be hard to teach to AI. De Bruyn et al. (2020) acknowledge that AI has limitations in domains where tacit knowledge is crucial. The traditional way of idea selection is that managers go over the transcripts and assign ratings to identify the best ideas (Urban and Hauser 1993). Sometimes, firms staff juries with high-profile experts from outside the firm to account for different perspectives (Bell et al. 2024) and heterogeneous experiences that provide a more complete picture.

How can AI facilitate these processes? Research is limited. Kornish and Ulrich (2014) suggest that success may depend on observable and latent features of the idea itself, for example, on its form and function. Kakatkar et al. (2020) derive such latent features of idea descriptions and link them to success indicators to automatize idea selection. In the only empirical study that uses AI according to our knowledge (see Table 5), Wei et al. (2022) study the success of over 98,000 crowdfunding projects on Kickstarter. They develop a new approach to measure the pairwise similarity between projects to construct similarity networks of projects. Funding success has an inverted U-shaped relation with project novelty.

Table 5 provides an overview of AI-related literature on idea screening and idea selection.

6.3 | Case Study Idea Screening Pfizer (Pfizer 2022)

> Pfizer's researchers now use cloud-based supercomputing with AI machine learning models to test a manageable fraction of the millions of compounds that might work as a new drug. Researchers can then focus on compounds with the highest chance of becoming medicines.

> The development of PAXLOVID shows the power of supercomputing and AI to accelerate drug research

TABLE 5 | Overview of AI-related literature on idea screening and idea selection.

	Article	Summary	Major findings
Idea Screening	Bell et al. (2024) *Marketing Science*	Extension of three existing theories and out-of-sample application to screen thousands of ideas from 21 crowdsourcing contests	• New approach screened 44% of bad ideas while only sacrificing 14% of good ideas • Development of idea screening efficiency curve as easy-to-use tool for managers • Development of a novel two-step approach that manages to screen > 20% of bad ideas without sacrificing a winner • Development of Word Atypicality (typical ideas are better than atypical ideas) as indicator for idea quality
	Lane et al. (2024) *Working Paper*	Investigation of human–AI collaboration in early-stage idea screening for social impact innovation. 3 scenarios: • human only • black box AI recommendations for human screeners • AI providing recommendations and rationales for decisions to human screeners	• Screeners validate AI's recommendations when they agree and scrutinize them when they disagree • Screeners assisted by AI are 9% more likely to fail a solution than the control recommendation, primarily influenced by AI's more stringent failure recommendations • Explanations for AI recommendations increase adherence by 12% compared with black box treatment • Effects were larger among community than expert screeners • AI explanations led screeners to over-rely on AI
	Hoornaert et al. (2017) *Journal of Product Innovation Management*	Identification of predictors for future implementation of ideas in a crowdsourcing community for an IT product	• Crowd feedback is the best predictor of idea implementation, followed by idea content and distinctiveness, and the contributor's past idea-generation experience • Idea screening/selection support systems: one to rank new ideas in real time based on content and contributor experience another that integrates the crowd's idea evaluation after some time for reaction
	Just, Hutter, et al. (2024) *Creativity and Innovation Management*	Use of transformer-based language models to reduce large sets of idea descriptions into manageable structures. Exploration of three search practices: direct search, cluster exploration, and pattern discovery	• Direct search identifies solutions that match pressing needs or subproblems • Cluster exploration aggregates semantically similar ideas to identify relevant needs • Pattern discovery synthesizes themes and interrelations to build a holistic understanding of potential solutions
	Just, Stroehle, et al. (2024) *Academy of Management Proceedings*	Analysis of solution landscapes depending on the semantic similarity of ideas. It examines how the similarity structures of ideas influence the likelihood of success	• Distinctive ideas are generally more successful, but associations are non-linear and context-dependent • Study highlights the importance of the density of the spanned landscape • In denser landscapes, distinctiveness in terms of Word Atypicality is negatively related to success • While highly interconnected ideas are more appreciated, ideas closely connected to others are less successful in dense contexts

(Continues)

TABLE 5 Continued

	Article	Summary	Major findings
	Rupp and Füller (2024) *Academy of Management Proceedings*	Exploration of the predictive power of AI-measured spontaneous effect on idea evaluation. Using affective computing, this study measures spontaneous affective reactions of potential customers to Kickstarter pitches	• Significant correlation between affect (measured as the interaction of valence and arousal) and idea evaluation, particularly in the context of hedonic products
	Rupp et al. (2023) *Academy of Management Proceedings*	60 evaluators watched 6 product pitches with ideas on how a major German electronics chain can better position itself in the well-being sector; analysis of facial expressions of participants with respect to valence and arousal	• Interaction of valence and arousal predicts idea evaluations and investment intentions • Valence/arousal alone does not
Idea Selection	Wei et al. (2022) *Journal of Marketing*	The authors study the success of 98,058 Kickstarter projects. They exploit the tension between novelty and familiarity. They develop a new approach to measure the pairwise similarity between projects to construct a similarity networks of projects	• Funding outcomes have an inverted U-shaped relation with project novelty • Optimal goal is close to the funds raised by past similar successful projects • Optimal goal is a balance between atypical and conventional combinations of past projects

> and discovery. Using modeling and simulation, Pfizer was able to screen millions of protease inhibitor compounds to arrive at potential targets. The firm used virtual screening to help select the right molecular changes to enhance potency and then factored the data into the decisions on which compounds to make.

6.4 | Potential Generalizations

- While there is an increasing amount of high-quality research on idea screening, research on idea selection remains limited.
- While idea screening will predominantly be performed by AI, AI will not yet fully replace experts in idea selection; that may change in the future.
- Emotions play a role in idea evaluation and can be captured by AI. Particularly, the interaction of valence (positive or negative emotions) and arousal (intensity of emotion) in predicting the evaluation of the idea (Rupp and Füller 2024; Rupp et al. 2023), mainly for hedonic products.
- AI explanations increase trust. If an AI explains the reasons for certain recommendations, screeners are more likely to follow them (Lane et al. 2024)

6.5 | Research Challenges

Table 6 provides an overview of research challenges in idea screening.

7 | Conclusion

7.1 | Summary

Innovation is of crucial importance for consumers, countries, and especially for firms (Hauser et al. 2006; Sorescu and Spanjol 2008). The advances in AI in recent years already have a tremendous impact on the innovation process in general—and on ideation in particular. As of 2025, AI fundamentally changes how business gets done (Dell'Acqua et al. 2023); it will impact how firms grow revenue, engage with customers, build new business models (PwC 2024) and innovate. Thus, 74% of all US firms have already adopted AI in at least some areas of their business (PwC 2024). Firms that embrace AI across processes like innovation and ideation benefit most and stay ahead of the market (Boussioux et al. 2023; Fountaine et al. 2021).

This article starts with a theoretical model on how AI mediates the effect of firm culture on innovation type, that is, radical versus incremental innovation, *across* firms; it then focuses on the innovation process *within* firms with a special emphasis on AI in ideation. Next, the authors review three fields of AI in ideation: identification and analysis of new opportunities, idea generation, and idea screening and idea selection. The results of our study are as follows. First, whereas in the past researchers highlighted the importance of industry characteristics and market stability, the authors now emphasize the importance of firm culture in driving radical innovation. AI will be an important mediator in this relationship. Second, across all stages, AI will improve the efficiency, speed, and cost of ideation. Third, in opportunity identification, considerable progress has occurred in analyzing text and image data but not video and

TABLE 6 | Overview of research challenges in idea screening.

Category	Idea	Research challenge	Data needed to address challenge	How to acquire data
Idea Screening	Application of Customer Needs for Idea Screening	As shown in Section 4, there is an increase in AI approaches to identify customer preferences and customer needs. See for example Timoshenko and Hauser (2019). For an overview see Hauser et al. (2023). To evaluate ideas, one could compare customer preferences with the ideas that were generated to address those preferences, for example via similarity metrics.	Depends on the specific approach that was used to identify customer needs. Data that analyzes whether the idea description aligns with customer preferences.	
	Accounting for the Future Market Focus of Ideas	The focus on future markets is an important indicator for successful ideas (Chandy and Tellis 1998; Tellis 2012). Using AI, one can predict scenarios of how markets will develop (see e.g., Matthe et al. 2023 from Section 4; with respect to technology see Mühlroth et al. 2023). Based on these predictions, one can develop silicon samples (see Sarstedt et al. 2024 for an overview) of customers using GPT-4 or other LLMs. The twist is that those simulated consumers possess knowledge and preferences that represent the future market instead of the current market. Those silicon consumers can then evaluate the ideas.	Depends on the specific approach that was used to predict the future market. On how to conduct a silicon sample see Sarstedt et al. (2024).	
	Screening for Technology Leaps in the Eyes of Experts	Ideas are bags of words (Bell et al. 2024; Toubia and Netzer 2017). Good ideas balance novelty and familiarity from the perspective of expert judges. When tracking the ideas in a community and contest (both, within each ideator and within contest), one could flag novel ideas that differ from all others to enter the evaluation stage. AI allows to assess the semantic similarity of ideas on a broader level than Toubia and Netzer's prototypicality, or one could consider the emotions idea descriptions trigger (cf. Rupp and Füller 2024). This replicates expert evaluations more broadly than Toubia and Netzer's stringent evaluation. To realize this project, one follows the steps outlined in Toubia and Netzer (2017).	• Idea descriptions from ideation contests or communities • Ideally: a few ideas that can be used to train the model on how the experts of those contests evaluate ideas: complexity, novelty, uniqueness, originality, market value, feasibility	• Data can be scraped from websites like InnoCentive • Generate ideas using GPT-4 or related

(Continues)

TABLE 6 Continued

Category	Idea	Research challenge	Data needed to address challenge	How to acquire data
	Developing Silicon Experts to Overcome Expert Scarcity	Bell et al. (2024) point out that experts are limited for many settings because industry knowledge often relies on personal expertise and is often tacit. To evaluate ideas, one could leverage LLMs to simulate silicon experts (cf. Sarstedt et al. 2024), i.e., agents with diverse characteristics (marketing managers, production managers, lead users, ...). Each agent then evaluates the ideas from one's own perspective and screens the worst ideas.	• Idea descriptions from ideation contests or communities • Performance benchmarks, i.e., knowledge about good and bad ideas • Ideally: information about success of ideas in subsequent stages of the innovation process	• Data can be scraped from websites like InnoCentive • Generate agents using GPT-4 or related • Success metrics can best be obtained from companies
	Comparing AI Methods for Idea Screening	One can evaluate ideas using different methods, for example LLMs, Deep Learning, or Support Vector Machines (Cui and Curry 2005). A straightforward research question which has not been addressed yet is, which of those models performs best for different types of innovations, i.e., incremental vs. radical innovations or more vs. less complex innovations.	• Idea descriptions from ideation contests or communities • Performance benchmarks, i.e., knowledge about good and bad ideas	• Data can be scraped from websites like InnoCentive • Success metrics can best be obtained from companies

audio. Fourth, in idea generation, AI increases the average creativity of ideas, but the effect on the generation of top ideas compared with humans differs between studies, likely dependent on prompting techniques. Fifth, AI assists very well in idea screening, but does not do a good job yet in idea selection. Sixth and most importantly, we are in the early stages of AI, which will greatly improve in the future. So, we expect AI has the potential to radically transform ideation, subject to a firm's culture of innovation.

We expect that by structuring and relating different topics and perspectives, this article will contribute to the development of research in AI, innovation, and marketing. Research at this intersection is interesting, exciting—and needed by practitioners. It solves relevant problems, uncovers relevant phenomena, and provides novel theory and potentially generalizable findings. However, interesting challenges remain to be addressed.

7.2 | Questions

AI can help in regard to the innovation process or innovation outcomes. Might AI's impact on the innovation process be consistent across the innovation stages while its impact on innovation outcomes be contingent on innovation stages? Indeed, AI's impact on the innovation process tends to be consistent across stages. The reason is that AI has a wide range of functions like data analysis, pattern recognition, predictive modeling, and the ability to generate text and image. Each of these functions may aid in the different stages of the innovation process from identification and analysis of new product opportunities to launch. In contrast, AI's impact on innovation outcomes may vary depending on the stage. In the early stages of the innovation process, for example, idea generation, AI might primarily enhance creativity; more ideas may increase the probability of one outstanding idea (Terwiesch and Ulrich 2009). In later stages, important benefits of AI could include efficiency or optimization of processes. Thus, innovation outcomes might be contingent on each stage's specific goals and AI's role in achieving them.

We have shown that culture is important. But what can companies actually do on a more operational level? Tellis (2012) provides a roadmap. For example, firms may embrace AI in the innovation process by building internal markets, adjusting incentives, identifying and enabling product champions, encouraging risk taking, spurring risk taking for AI on innovation projects if they further want to explore, and exploiting the opportunities AI offers.

This study applies well to B2C markets. Would these results apply to B2B innovation, noting here that B2B is a very substantial market? What might be the sources for differences? We think that not all results presented may generalize to B2B settings. Differences between B2C and B2B markets include the type of customer interactions, product complexity, and relevance of functional versus emotional product dimensions.[2] Some results are generalizable to B2B, for example, AI will improve efficiency, speed, and cost of ideation. Others may be less generalizable. The reason is that in B2B settings, multiple decision makers of suppliers and customers may agree on complex tailored solutions that involve technical and regulatory requirements. In such cases, ideation is less an open search for the best ideas (cf. Bayus 2013; Pescher et al. 2025), but rather for problem solving under complex restrictions. Whether simple approaches like Word Atypicality (Bell et al. 2024; Just, Stroehle, et al. 2024) can help to screen ideas remains subject to future research—but should not be taken for granted.

What are the implications related to increased time and costs associated with handling AI-generated information overload? AI can generate a very high amount of information, for example, a much higher number of ideas in idea generation than human evaluators can handle. Consequently, Girotra et al. (2023) state that the critical task moves from idea generation, that is, the generation of information, to idea screening, that is, the reduction of information. For example, an early AI-based idea screening mechanism developed by Bell et al. (2024) screens almost half of the bad ideas, without losing many good ones, which substantially reduces the cognitive burden on expert evaluators. Likewise, AI does a terrific job in summarizing and classifying information. So, if managers set the right priorities, AI mitigates the problem of information overload.

Ethics Statement

The authors have read and agreed to the Committee on Publication Ethics (COPE) international standards for authors.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

We do not use empirical data.

Endnotes

[1] Supporting Information Appendix A contains a more extensive version of this model. In the interest of space, we limit the in-depth discussion on culture and AI.

[2] Differences between B2C and B2B markets include the type of customer interactions (B2B: personal relationships are more important, much fewer relationships, much closer cooperations between buyer and seller that often lead to tailored solutions); product complexity (B2B: multiple stakeholders on both sides, more complex processes); and relevance of functional versus emotional dimensions of the product (B2B: functional performance and economic value are much more important than in B2C; B2C: emotional dimensions and brands are more important).

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Supporting Information

Additional supporting information can be found online in the Supporting Information section.