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ORIGINAL EMPIRICAL RESEARCH

# Generative AI in innovation and marketing processes: A roadmap of research opportunities

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**Abstract**
Nowadays, we are witnessing the exponential growth of Generative AI (GenAI), a group of AI models designed to produce new content. This technology is poised to revolutionize marketing research and practice. Since the marketing literature about GenAI is still in its infancy, we offer a technical overview of how GenAI models are trained and how they produce content. Following this, we construct a roadmap for future research on GenAI in marketing, divided into two main domains. The first domain focuses on how firms can harness the potential of GenAI throughout the innovation process. We begin by discussing how GenAI changes consumer behavior and propose research questions at the consumer level. We then connect these emerging consumer insights with corresponding firm marketing strategies, presenting research questions at the firm level. The second set of research questions examines the likely consequences of using GenAI to analyze: (1) the relationship between market-based assets and firm value, and (2) consumer skills, preferences, and role in marketing processes.

**Keywords** Generative artificial intelligence · Innovation · Marketing strategy · Marketing capabilities · Firm value

## Introduction

Generative AI (henceforth, GenAI) represents the latest evolution in the field of Artificial Intelligence (AI) and is a group of AI models designed to generate new content, spanning text, images, and videos (Huang & Rust, 2023). According to a recent McKinsey report, marketing is projected to be the most affected firm function by GenAI, which is forecast to enhance marketing productivity by up to 15% of the total marketing expenditure, amounting to approximately $463 billion annually.[1] While AI has changed marketing activities in several ways, ranging from product personalization (Chung et al., 2016) to service experience (Noble & Mende, 2023), one of the most distinctive features of GenAI is its capability to create novel content (Eapen et al., 2023). Unsurprisingly, numerous firms have already started using GenAI to perform key innovative marketing activities. For instance, Coca Cola used GenAI to co-create new beverages, such as its Coca-Cola Sugar Y3000. Similarly, companies like Unilever, Nestlé, and Mondelez have been using GenAI to create advertising.[2] Despite the disruptive potential of GenAI in marketing, the marketing literature that explores the impact of GenAI for consumers and firms is still nascent (Huang & Rust, 2023; Li et al., 2024; Reisenbichler et al., 2022), thus prompting this effort to propose a roadmap that describes both GenAI's current status as well as its potential to impact consumer and firm behavior in innovation and marketing processes.

We start with a brief overview of the technical specificities of GenAI, as well as its capabilities and current

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1 https://www.mckinsey.com/capabilities/growth-marketing-and-sales/our-insights/.how-generative-ai-can-boost-consumer-marketing.

2 https://www.theverge.com/2023/8/18/23837273/generative-ai-advertising-oreos-cadbury-watermarking.

limitations. Then, we propose research opportunities across two main domains. First, we focus on GenAI's potential to alter both internal marketing activities that mainly deal with innovation, as well those interface activities for which firms try to leverage consumers' creativity. With our research questions, we aim to investigate how GenAI can impact the entire innovation process, distinguishing among four phases: *developing*, *testing*, *communicating*, and *engaging* with the firm's innovative output (Knight, 1967; Mumford & Simonton, 1997; Rubera et al., 2016). We validate these research questions via in-depth interviews with managers from different industries, spanning from high-end fashion and fast-moving consumer goods to insurance and utilities. These interviews reveal that, beyond their interest in understanding how to harness the innovative potential of GenAI, managers are concerned with the effects of repeatedly using GenAI on marketing capabilities and consumer behavior. Thus, we develop a second set of research questions to investigate the consequences of repeated GenAI use by firms and consumers. For firms, we develop questions related to the effects of employing GenAI on how marketing contributes to create firm value. Similarly, for consumers, we offer research questions related to the potential impact of GenAI on consumer skills, preferences, and role in the marketing processes.

This paper makes two main contributions to the marketing literature. First, several papers have offered a research map for the applications of AI in marketing (Davenport et al., 2020; Huang & Rust, 2021; Puntoni et al., 2021). These papers mainly investigate either mechanical or thinking AI (Huang & Rust, 2021). However, GenAI is a different type of AI that is poised to transform marketing in a completely different way. Recently, Huang and Rust (2023) have analyzed how GenAI can be used to move the customer along the customer care journey. They consider GenAI as the most advanced, so far, form of feeling AI. Complementing their perspective, we analyze the impact of GenAI on a different yet fundamental activity for firms (i.e., innovation). Second, previous papers outlining research questions about the effect of AI on marketing have focused on either the consequences on firms' activity (Davenport et al., 2020; Huang & Rust, 2021, 2023) or consumer response (Puntoni et al., 2021). This article aims to bridge these two perspectives by developing research questions both at the consumer and firm level. At the consumer level, we focus on how GenAI can impact consumers' creative behavior. Since firms try to leverage consumer input throughout the innovation process, we maintain that analyzing the potential impact of GenAI on consumers' creative behavior is a prerequisite for investigating the impact of GenAI on the firm innovation process (Hamilton, 2016). In this way, we hope that this roadmap can help marketing scholars pursue research across various areas of specialization.

## GenAI: A technical overview

In technical terms, we can define GenAI as deep neural networks, pre-trained on large amounts of data to create a foundation model, which is then fine-tuned to produce new content by following human instructions (Bommasani et al., 2021). In this section, we provide a technical overview of how GenAI models are trained and how they produce content. Given these technical specificities, we then explain why the output of GenAI can be helpful for firms, as it is both novel and appropriate–and, hence, creative (Amabile, 2018; Scopelliti et al., 2014).

### Training on extensive, unannotated datasets: Self-supervised learning

GenAI is the outcome of a renewed focus on *self-supervised* machine learning rather than the supervised learning approach that characterized much previous AI developments (Bommasani et al., 2021). In a supervised learning approach, during the training, machines learn by comparing model output against a given correct answer. These correct answers are provided in forms of "labels" or "annotations," which require human involvement in labor-intensive tasks. The significant cost of annotation severely restricts the volume of data available for model training, limiting the ability to generalize effectively to novel settings (Bommasani et al., 2021).

In contrast, self-supervised learning models are trained with no need for annotated datasets. Instead, training occurs by removing parts of the data and asking the model to "predict" the missed parts. For instance, with textual data, we can input a sentence like "This is a <…> article" and train a model to predict the omitted word, given its surrounding text. At the end of the training, the model should have learned that the words "review" or "scientific" are more likely to be omitted compared to, say, "umbrella." Similarly, with images, we can mask some patches and train a model to predict the content in the masked patches based on the remaining image information.

Self-supervised training yields two direct consequences that define GenAI's ability to generate new, plausible content. First, since the original data contains the correct part to predict (i.e., the missing part), the training process can scale to very large datasets, which would be challenging to annotate by hand. These large datasets come in many forms, such as text, images, audio recordings, and videos. Second, by being forced to predict parts of the inputs, self-supervised learning models develop a deeper understanding of the context. This enhanced understanding, coupled with training on significantly larger datasets, makes it easier to generalize to novel settings than was the case with past, supervised AI models.

## Producing new content: Inherently random and conditional on the prompt

The adoption of a self-supervised learning approach, coupled with advancements in computing power (e.g., GPU) and a novel model architecture known as Transformer (Vaswani et al., 2017) that allows faster training, led to the emergence of *foundation models*. A foundation model is a large, pre-trained model used as a base for developing more specialized and task-specific models (Bommasani et al., 2021). Foundation models underpin generative capabilities. Specifically, they create new content (e.g., text, image, video, data) by using patterns learned during training to predict the next item in a sequence. For instance, OpenAI and Microsoft have deployed GPT-3 in a variety of downstream tasks, such as Bing, Duolingo, GitHub Co-pilot, and ChatGPT. To understand how foundation models produce new content, let us take the example of Large Language Models (LLMs), a subset of foundation models that have gained significant prominence as they are trained to facilitate user interaction through natural language. A language model (LM) is a statistical representation of a language, which computes the probability of a given sequence (a word, phrase, or sentence) occurring in this language. Similar to LMs, LLMs are trained in a self-supervised logic to predict a masked word within a sequence of words. Because they are trained on large amounts of data as well as frequently trained on different languages, they are called *Large* LMs. If we consider words and punctuation signs as tokens, we can depict an LLM as a conditional probability distribution $p(x_n|x_1, \ldots, x_{n-1})$ over tokens, in which each $x_i$ is drawn from a fixed vocabulary. An LLM generates text by iteratively sampling from the learned distribution to select the next token. At each generative iteration, the model estimates a probability distribution, indicating the likelihood that any token in the vocabulary would be the next observed $x_i$ if the model were reading a pre-existing text. To initiate text generation, an LLM requires "conditioning," meaning it must be supplied with initial input tokens $x_1, \ldots, x_{n-1}$. Such input is called *prompt*. The prompt conditions the probability of selecting one token over another. For instance, if we input the prompt "This is a review…," the token "article" would have a higher probability of selection than the token "bus." Using a distribution function, the model *randomly* selects among a list of probable candidates (e.g., "article," "paper"). The new $x_i$ is then added to the text, initiating the repetition of the entire process (Argyle et al., 2023). The generation of novel images, music, videos, or data follow a similar approach.

Thus, GenAI outputs novel content that is conditional on the prompt that it receives. Given how foundation models choose the next word, note, or image feature, such content however is random and different at each iteration, making it possible to produce several, unique responses from the same prompt. This inherent randomness explains why it is hard to detect content generated by GenAI (Else, 2023).

In sum, training foundation models is a highly resource-intensive process that demands substantial computational power and can take months to complete. For instance, it is estimated that the cost of training GPT-4 is over $100 million (Korinek, 2023). However, while training GenAI is financially viable for only a handful of companies, use costs are very low. Thus, firms no longer compete on developing proprietary machine learning and AI algorithms, but rather on their ability to fully harness the capabilities of existing foundation models.

## The potential of GenAI for marketing and innovation

Having reviewed how GenAI models are trained and how they produce new content, we next describe the capabilities and current limitations of these models. Huang and Rust (2023) conceptualize GenAI as feeling AI, namely a type of AI that can communicate and interact with humans based on an emotional understanding derived from analyzing emotion data. They argue that these models differ from previous AI models, which were better suited for mechanical AI (i.e., performing repetitive tasks) and thinking AI (i.e., supporting analytical decisions) (Huang & Rust, 2021). We embrace their view of GenAI as a novel type of AI; to complement this view, we focus on GenAI's capability to create new content. Since we are interested in how firms can leverage GenAI in their innovation and marketing processes, we examine whether GenAI's output can be both novel and appropriate, two key elements that influence consumer evaluations of new products, marketing programs, and advertisements (Rubera et al., 2010).

The associate theory of creativity maintains that novelty stems from the ability to connect weakly related concepts to form novel ideas (Dahl & Moreau, 2002; Toubia & Netzer, 2017). Since foundation models have been trained on extensive datasets, these models can retrieve concepts from a vast array of diverse domains. Leveraging this capability, scientists started exploring how LLMs can be used to discover new hypotheses to test (Hutson, 2023). The inherent randomness in the way foundation models produce content is a prerequisite for identifying this output as novel. Indeed, throughout history, significant innovations have emerged as serendipitous discoveries, ranging from medical breakthroughs (Meyers, 2007) to new consumer products like Post-its or shatter-proof glass.

However, randomly connecting concepts from different domains is not sufficient per se for generating something that consumers appreciate; rather, this content must also be appropriate (Rubera et al., 2010). Since foundation models have been trained on extensive datasets, it is very likely that they have memorized in the training phase what humans consider to be appropriate. Girotra et al. (2023) conducted a comparative study, pitting a pool of ideas generated by MBA students against those generated by ChatGPT-4 in two distinct conditions. In the baseline condition, ChatGPT-4 received an identical prompt to that of the MBA students (i.e., generate ten ideas targeting college students in the U.S.). In the "prompted with good examples" condition, the authors supplemented the prompt with a set of highly rated ideas. They find that ideas generated by ChatGPT-4, regardless of the condition, exhibit higher average scores on purchase intentions compared to ideas generated by MBA students. Interestingly, they report no significant difference between the two GPT conditions (i.e., baseline versus prompted with highly rated ideas). A possible explanation for this finding is that GPT had already seen those highly rated ideas (or, at least, similarly appropriate ideas) during the training. Thus, providing further examples of good ideas in the prompt is redundant, as GPT has already memorized what humans consider to be appropriate.

In sum, the stochastic nature of foundation models enables them to generate novel content. The extensiveness of the data they have been trained on allows this novelty to also be appropriate.

## Current limitations of GenAI

Although GenAI is able to create new content, it sometimes produces content that, while semantically or syntactically plausible, is factually incorrect or nonsensical (i.e., hallucinations) (Huang & Rust, 2023). For instance, on February 6, 2023, Google announced its ChatGPT competitor named Bard with an image of Bard answering the question "What new discoveries from the James Webb Space Telescope can I tell my 9 year old about?" As several astronomers pointed out, one of the three replies that Bard provided was factually wrong. As a consequence, Google stocks lost $100 billion. Similarly, just two weeks before OpenAI launched ChatGPT, Meta released Galactica, which the company positioned as a "large language model for science." The open source LLM survived for only three days before Meta withdrew it in response to criticism for releasing a model that produced scientific-sounding text but that was nonetheless factually wrong. Capitalizing on Galactica's failure when it launched ChatGPT, OpenAI explicitly acknowledged that it could make mistakes. The Bard and Galactica cases clearly indicate the limitations of initial GenAI. It works better when it is tasked with generating novel content for which there are no right or wrong answers (e.g., artistic content, novel product ideas).

To help marketers apply GenAI effectively, we provide in Table 1 a summary of studies that investigate GenAI's emergent capabilities that are most closely related to innovation. These capabilities include idea generation, divergent thinking, analogical thinking, and inductive reasoning, which are all traditionally considered prerequisites for creativity (Dahl & Moreau, 2002; Vartanian et al., 2003). Additionally, our interviews reveal that an increasing number of managers rely on GenAI, or wish to, for decision-making support. Therefore, we also focus on capabilities related to reasoning, such as causal reasoning, logical reasoning on new cases, and making causal inferences.

Since different foundation models are trained on different data and have different architectures, and also since the same released model can be updated over time, we report the model used and time of the test. Table 1 indicates that current models have limited reasoning capabilities with respect to making causal inferences. Computer scientists attribute hallucinations and these limitations to the absence of physical data in most GenAI models, which constrains their understanding of the world (Webb et al., 2023; Zečević et al., 2023). Indeed, most studies conducted so far have focused on LLMs trained exclusively on text-based inputs, which lack embodiment, sensory stimuli, or grounded experience that are crucial for human decision-making (McClelland et al., 2020). However, the emergence of multimodal models like GPT-4 V(ision) (i.e., capable of processing text, image, sound, and other sensory data) may pave the way for GenAI to develop a more integrated understanding of the world (McClelland et al., 2020; Webb et al., 2023). Thus, we note that GenAI is rapidly evolving and that these limitations could potentially be addressed in the future.

## Research opportunities

Given our focus on GenAI's capability to create new content, we propose research opportunities related to how firms can harness the innovative potential of GenAI throughout the firm innovation process. Consistent with past views of the innovation process (Knight, 1967; Mumford & Simonton, 1997; Rubera et al., 2016), we depict this process as a circular one that encompasses four main stages–developing, testing, communicating, and engaging–during which firms interact with customers to gain different types of input, ranging from creativity to customer knowledge.

**Table 1** Emergent capabilities of GenAI

| Capability | Main finding | Reason | Source | Model and Test-time |
|---|---|---|---|---|
| Generate ideas for new products | GenAI generates ideas that receive higher purchase intentions by potential consumers | In creative problem-solving, variability in quality, and productivity (i.e., the number of ideas generated) are more valuable than consistency | Girotra et al. (2023) | ChatGPT-4 (July 2023) |
| Divergent thinking | GenAI is better than humans on average, but not consistently better than best human performers | **Speed** in accessing **large data structures** | Koivisto and Grassini (2023) | ChatGPT3 (30.3.2023) ChatGPT4 (5.4.2023) Copy.Ai (1.4.- 2.4.2023) |
| Analogical reasoning | GenAI solve analogies through associative process (like children do) rather than through relational mapping (like adults do) | LLMs relies on **semantic similarity** between analogy terms | Stevenson et al. (2023) | Different LLMs (October 2023) |
| Inductive reasoning | GenAI matches human performance | GenAI fails to reason about how the premises of an inductive argument are generated | Han et al. (2024) | gpt-4-0314 (March 2024) |
| Causal reasoning | GPT3 often showcase human-like biases in causal reasoning tasks | LLMs might have **memorized answers during training** or they could follow human-like cognitive processes | Binz and Schulz (2023) | OpenAI GPT-3 models |
| Logical reasoning on new cases | GenAI attains near-perfect accuracy on in-distribution test examples while failing to generalize to other data distributions over the exact same problem space | Instead of learning the correct reasoning function, LLMs have learned **statistical patterns** in logical reasoning problems | Zhang et al. (2022) | BERT (August 2023) |
| Making causal inferences | LLMs perform well on causal inference tasks only occasionally | Current LLMs are **unable to process physical data** measurements to ground their available textual facts | Zečević et al. (2023) | GPT-3 (August 2023) Luminous (August 2023) OPT (August 2023) |

*Notes* We report the date of the test because foundation models (such as GPT) change with no announcement and provide different results over time

We validated these research questions via in-depth interviews with managers from different industries, spanning from high-end fashion and fast-moving consumer goods to insurance and utilities. They point out that firms' repeated use of GenAI will fundamentally alter marketing capabilities, for instance by making some of them obsolete or less valuable. Also, they expect that consumers' skills and preferences will likely change as an effect of widespread GenAI use. Thus, they fear that firms will necessarily face a very different customer in the near future. The inputs from practitioners motivated us to complement our framework with research questions about the consequences of GenAI use, both for a firm's market-based assets, marketing capabilities, and resources, as well as for consumer skills, preferences, and role in the marketing processes. We present our roadmap in Fig. 1.

## Harnessing the innovative potential of GenAI

Our framework views the innovation process as a circular process that encompasses several interactions with customers throughout the four stages. In the developing phase, firms frequently involve consumers in co-creation activities through open innovation platforms and crowdsourcing initiatives (Bayus, 2013; Cillo et al., 2021; Luo & Toubia, 2015; Rubera et al., 2016; Stephen et al., 2016). These initiatives aim to augment internal creativity with customer ideas. In the testing stage, firms conduct market research to gain customers' perspective in order to select the one with the best chances of meeting market needs, given the various inputs generated in the previous phase (Kahn et al., 2006). In the communicating stage, firms interact with customers to persuade them to change their behavior and adopt the firm's offering (Castaño et al., 2008). After consumers buy the firm's novel offering, firms continue interacting with customers to keep them engaged beyond economic transactions (Blut et al., 2023; Pansari & Kumar, 2017). This engagement enables firms to access key consumer resources (e.g., knowledge stores, creativity) (Harmeling et al., 2017) that offer further creative input to the innovation process, thus constituting a continuous cycle, as illustrated in Fig. 1.

For each phase, we start by discussing the potential impact of GenAI on consumer behavior and propose consumer-level research questions. The only exception is the testing stage in which, as we will discuss, GenAI can help firms partially replace customer inputs when conducting market research. These customer insights help us investigate how firms can harness the innovative potential of GenAI. In so doing, we bridge these emerging customer insights with corresponding firm marketing strategies, presenting research questions at the firm level (Hamilton, 2016). We summarize our proposed research questions in Table 2.

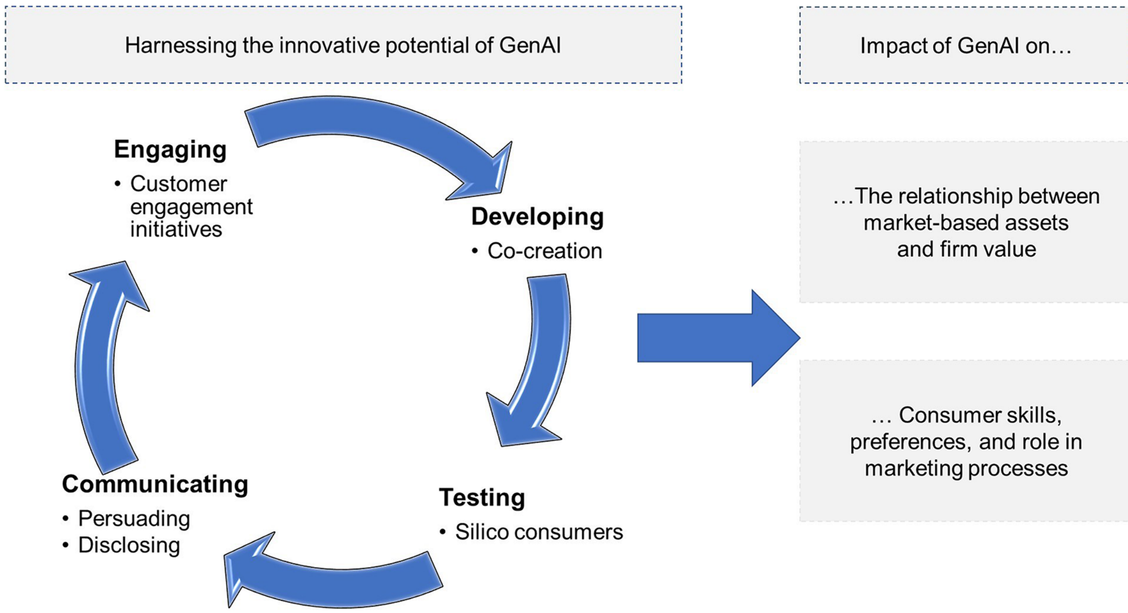


**Fig. 1** GenAI in innovation and marketing processes

**Table 2** Harnessing the innovative potential of GenAI: Research questions

| Phase of the innovation process | Level of analysis | Research questions |
|---|---|---|
| Developing | Consumer | • Through what cognitive mechanisms does GenAI influence the creativity of an individual consumer?<br>• Do different consumers follow different cognitive mechanisms?<br>• What individual traits and contextual factors influence consumer inclination to either conform to or diverge from GenAI solutions? |
| | Firm | • How can firms design co-ideation platforms to reduce the AI-conformity effect? |
| Testing | Firm | • What market research can be conducted with GenAI rather than human participants or experts?<br>• What are the boundary conditions of GenAI's capability to replace human subjects/experts in market research?<br>• How can we assemble different LLMs to better replicate human /expert responses? |
| Communicating (Persuading) | Consumer | • Does variation in objective LLM parameters translate into differing subjective perceptions of persuasiveness?<br>• What are the theoretical mechanisms through which objective LLM parameters influence subjective perceptions?<br>• What theoretical constructs cause heterogeneity in consumer responses to variations of objective LLM parameters? |
| | Firm | • How can firms vary LLM parameters to create more persuasive messages?<br>• Which LLM parameter is most conducive to different marketing goals? |
| Communicating (Disclosing) | Consumer | • Do consumers respond differently to the disclosure of GenAI compared to the disclosure of other types of AI?<br>• What novel theoretical mechanisms explain consumer responses to a firm's disclosure of GenAI-generated content? |
| | Firm | • Which brand associations amplify the negative effect of GenAI disclosure on brand equity? Which associations mitigate this effect?<br>• How can firms align disclosure messages to their firm brand associations to mitigate the potential negative effect of disclosing GenAI use? |
| Engaging | Consumer | • What are the consequences of employing GenAI tools for consumers working on customer engagement initiatives? |
| | Firm | • What novel, task-based customer engagement strategies can firms pursue using GenAI?<br>• How can firms manage the trade-off between wider reach and customer engagement of GenAI, task-based initiatives? |

## Developing

In the past decade, firms have devoted much effort in involving consumers in the idea development phase through open innovation platforms and crowdsourcing initiatives (Bayus, 2013; Luo & Toubia, 2015; Stephen et al., 2016). Through these initiatives, firms outsource to consumers either part of or the entire creative process, which comprises two cognitive, iterative processes: generative and exploratory (Moreau & Dahl, 2005). In the generative stage, preliminary mental representations of a solution are created. In the exploratory stage, these representations are evaluated. If the exploration is not successful, a new generative stage occurs until a satisfactory idea is achieved.

While past studies investigated how AI can enhance idea screening (Bell et al., 2023), GenAI can clearly support participants in the idea-generation phase. Specifically, GenAI can potentially decouple the two cognitive processes that underpin creativity: it can create differing solutions (i.e., generation), while consumers then can be solely responsible for modifying the proposed solutions (i.e., exploration). In this case, we envision an iterative process in which consumers engage in a conversation with GenAI to refine the created solutions until a satisfactory idea emerges. Future research is needed to investigate the consequences of this decoupling at both the consumer and firm level.

At the consumer level, the literature indicates that people's ideas are influenced by those around them who are working on the same task (Mason & Watts, 2012; Stephen et al., 2016). Exposure to others' ideas might lead consumers to engage in either cognitive fixation (Bayus, 2013) or cognitive stimulation (Luo & Toubia, 2015). Thus, we can expect consumers to either *conform* to a GenAI suggestion or further *diversify* in their efforts to reaffirm their diversity from machines. We theoretically expect that both conforming and diversifying consumers achieve higher levels of creativity when supported by GenAI, but through two different mechanisms.

Conforming consumers outsource the generative stage to GenAI. Since GenAI is trained on very diverse data, it can provide conforming consumers with more diverse, initial representations of a solution from which these consumers can select in the exploratory stage. Since they can select from a wider pool of ideas, doing so should translate to a final solution that is more creative than if consumers had no access to GenAI input (Dahl & Moreau, 2002). In contrast, diversifying consumers engage further in the generative stage in order to find more initial representations that differ from GenAI input. This extra cognitive effort would encourage diversifying consumers to explore more distant alternatives, thereby increasing the creativity of the final solution (Luo & Toubia, 2015). However, future research is needed to empirically investigate the mechanisms that increase the creativity of the final, GenAI-augmented solution for different types of consumers:

**RQ** Through what cognitive mechanisms does GenAI influence the creativity of an individual consumer? Do different consumers follow different cognitive mechanisms?

Luo and Toubia (2015) show that domain knowledge determines whether consumers fixate with others' ideas or not. Lysyakov and Viswanathan (2023) find that prior success determines whether designers conform or diversify in response to the introduction of an AI system for logo designs in a crowdsourcing design platform. Thus, future research should investigate the elements (individual or contextual) that encourage consumers to either conform or diversify to solutions proposed by GenAI:

**RQ** What individual traits and contextual factors influence a consumer's decision to either conform to or diverge from GenAI solutions?

At the firm level, the path that consumers pursue (i.e., AI conformity or diversification) has direct consequences on the *collective* creativity of the pool of co-produced ideas from which a firm can select, which is a key output of co-ideation initiatives. Since consumers who conform select solutions from the same (or similar) GenAI-generated content, it is likely that these conforming consumers end up generating similar content, as they are anchored to the same set of GenAI-generated ideas. Indeed, studies on ideation platforms have shown that when customers draw inspiration from similar sets of ideas, they tend to develop less innovative ideas (Stephen et al., 2016). If this is the case, then co- ideation initiatives bear ideas that are not creative enough to warrant further internal development, a common problem for these initiatives (Stephen et al., 2016). To curb this drawback, scholars suggest that firms limit the quantity of others' ideas that participants can access (Luo & Toubia, 2015; Stephen et al., 2016). Such a feature is clearly not possible for GenAI, as consumers access it on their own device. Further, the fact that consumers conform to solutions proposed by GenAI defies the purpose of co-ideation initiatives: employees within the firm can access these ideas directly without tapping into consumers' creative resources. Huang and Rust (2023) propose an intriguing approach, which they call *response engineering*, in which GenAI probes consumers' preferences iteratively through multiple rounds of question-asking. Firms could employ a similar response engineering approach in which GenAI asks questions (rather than provides answers) that would nudge consumers to deviate from the original idea in order to help them develop, at each iteration, more creative ideas. That said, this is a workaround solution at the moment because GenAI is not designed to ask questions (Huang & Rust, 2023). Thus, future research should investigate:

**RQ** How can firms design co-ideation platforms to reduce the AI-conformity effect?

## Testing

The generation phase is typically considered a *variation* phase, during which firms are concerned with simply generating as much creative input as possible (Girotra et al., 2010). In the next stage, a *selection* process starts, which is aimed at selecting the idea with the highest chance of gaining market acceptance once it is introduced in the market (Girotra et al., 2010). To do so, firms conduct market research (Kahn et al., 2006). The latest research on GenAI suggests that this technology can offer firms several ways to conduct market research.

Marketing research has shown how AI can lead to biased outcomes in service (Ukanwa & Rust, 2020) or ad delivery (Lambrecht & Tucker, 2019). Such bias derives from "algorithmic bias," in which machine learning models tend to replicate the gender, race, and economic biases of the data upon which they have been trained (Davenport et al., 2020; Plangger et al., 2022). However, LLMs have been trained on a vast set of diverse data, which means that they potentially could have memorized several biases, not just one. If true, then researchers can take advantage of this variety of biases to replicate different marketing sub-populations of consumers (i.e., different consumer segments). Investigating this possibility, Argyle et al. (2023) show that LLMs are characterized by what they call *algorithmic fidelity*: namely, "by conditioning a model on simulated 'individuals' with targeted identity and personality profiles," it is possible to gain insights "into different patterns of attitudes and ideas present across many groups (e.g., women, men, White people, people of color, millennials, baby boomers) and also the combination and intersection of these groups (e.g., Black immigrants, female Republicans, White males) (p. 338)." Leveraging algorithmic fidelity, Argyle et al. (2023) show that, by providing a prompt that describes the sociocultural characteristics of a specific demographic group, it is possible to generate response distributions that strongly correlate with that group's survey response distributions. Similarly, Horton (2023) demonstrates that various LLMs from OpenAI respond to economic scenarios in ways that are consistent with intuition and experience.

Algorithmic fidelity paves the way for marketers to potentially conduct market research with fewer requirements to involve human subjects. Indeed, an emerging body of studies has begun investigating how LLMs can substitute for market research. Brand et al. (2023) show that when prompted as if it were a randomly selected customer, GPT generates responses that exhibit sloped demand curves, lower sensitivity to changes in price as income increases, and state dependency (i.e., inertia in their product choice), all three of which are well-known features of real customers. Given these characteristics, the authors show that GPT generates estimates that are similar to those generated by human-based conjoint studies; they thus conclude that GenAI can represent a viable alternative for learning about consumer preferences in a fast, low-cost, and iterative way. Similarly, Li et al. (2024) show that GPTNeo and GPT4 can successfully match perceptual maps obtained from human surveys. The authors also show that these two GenAI applications can replicate survey differences along demographic variables and across time. Finally, Ringel (2023) investigates whether ChatGPT-4 can act as a surrogate for human expertise in classifying tweets that discuss marketing mix variables. He finds strong agreement between labels provided by ChatGPT4 and those provided by experts across all four metrics of the marketing mix, while labels provided by Amazon mTurk workers exhibit substantially lower agreement with expert labels. He concludes that "generative AI is a viable alternative to scarce and costly domain experts for labeling text."

Collectively, this emerging research suggests that GenAI can substitute, at least in some cases, for human subjects and experts in marketing research. It is, thus, important to investigate what other marketing variables or constructs marketers can obtain through GenAI that will reduce the need to refer to surveys, focus groups, or expert opinions. Thus, we propose the following research question:

**RQ** What market research can be conducted with GenAI rather than human participants or experts?

As research about GenAI's capability to replace human subjects emerges, it is important to keep in mind that this capability depends on the training data of the foundation model deployed to "conduct" market research. Indeed, Horton (2023) infer from OpenAI's GPT replies that these LLMs must have been trained on a corpus more comparable to revealed preferences than to stated ones. Also, Li et al. (2024) report that LLMs work better for higher involvement products and for some brands than others. We speculate that this finding is due to the fact that GPT4 has more product reviews for these products in its training sample. However, future research is needed to determine which product categories/brands GenAI is better suited to replace human subjects /experts:

**RQ** What are the boundary conditions of GenAI's capability to replace human subjects/experts in market research?

Finally, Hartmann et al. (2023) show that images generated by different LLMs display significantly different performance in terms of click-through rates. The classic approach in marketing has been to compare different models in order to select the best one. We propose a different approach that is based instead on assembling predictions of different LLMs. Indeed, each LLM has been trained using different datasets, architectures, and hyperparameters, implying that each LLM has heterogeneous expertise in different tasks and domains, as well as idiosyncratic strengths and biases. Thus, assembling different LLMs can potentially harness the diverse strengths of each model, while exploiting the complementarities between them. Although the computer science community has started investigating different ways to assemble LLMs (Jiang et al., 2023; Lu et al., 2023), the ensemble method used always depends on the task at hand (Yang et al., 2023). Hence, it is important that marketers develop their own ensemble method that accounts for domain-specific goals. Thus, we propose the following research question:

**RQ** How can we assemble different LLMs to better replicate human/expert responses?

This argument suggests that the true potential of GenAI is represented by the combination of different LLMs, not an individual model. As such, we warn scholars intending to compare human performance with that of GenAI that a fair comparison should always require assembling different foundation models.

## Communicating

Gartner predicts that GenAI will produce 30% of brands' marketing messages by 2025,[3] thanks to GenAI's ease of use, multimodality (i.e., capability to integrate various types of data like text and images), and scalability. We pinpoint two crucial areas deserving further investigation: (1) the extent to which firms can rely on GenAI to convincingly *persuade* consumers, and (2) the consequences of *disclosing* GenAI use for a firm's brand equity.

### Persuading consumers

A key marketing activity involves crafting persuasive marketing content. GenAI potentially excels in this task due to its ability to swiftly generate new content at minimal marginal cost. Meta, for instance, has announced its intention to use GenAI for automatically creating ads.[4] So far, there is limited research that explores consumer responses to GenAI-generated content. Bai et al. (2023) and Kreps et al. (2022) in political science, and Zhang and Gosline (2023) in decision making represent notable exceptions. Interestingly, these studies report differing findings. While Bai et al. (2023) and Kreps et al. (2022) report no difference between GenAI and human-generated text, Zhang et al. (2022) find that ChatGPT-4 creates messages associated with higher satisfaction and willingness to pay than those produced by humans, even experts.

These initial studies aside, we argue that further research is necessary to examine the connection between GenAI's objective parameters and human subjective perceptions of its output. For instance, users can control the behavior of LLMs in three main ways. First, we have discussed earlier the relevance of *prompts*. Second, users can adjust the level of randomness (or creativity) in the output generated by modifying the *temperature* parameter. A temperature of 0 makes the model deterministic, always selecting the most likely token. As the temperature increases, the model becomes more random, leading to more diverse and creative output. Third, users can employ *top_p sampling* to restrict the model's selection to a subset of tokens (the nucleus), rather than considering all possible tokens. For instance, setting a *top_p* value to 0.2 means that the model will only select from those tokens that represent the top 20% of the probability mass for the next token. Given these technical nuances of GenAI, we identify avenues for future research, both at the consumer and firm level.

At the consumer level, the limited research on persuasiveness of GenAI-created messages has primarily focused on prompt strategies (Karinshak et al., 2023), with limited attention given to the role of temperature and top_p sampling. Hence, future research should explore whether variations in the objective parameters of LLMs are associated with variations in subjective evaluations of message persuasiveness. Learning more about this aspect could be crucial for crafting messages that are consistent with recipients' psychological characteristics. Thus, we propose the following research question.

**RQ** Does variation in objective LLM parameters translate into different subjective perceptions of persuasiveness?

Second, initial studies have started to explore differences in GenAI-generated content compared to that generated by humans. Bai et al. (2023) find that humans perceive messages crafted by GenAI to be more factual and logical but

[3] https://www.gartner.com/en/topics/generative-ai.

[4] https://techcrunch.com/2023/04/05/meta-wants-to-use-generative-ai-to-create-ads/?guccounter=1.

also less angry and likely to rely on vivid story-telling. Karinshak et al. (2023) report that GPT3-crafted pro-vaccination messages are perceived as more colloquial, authentic, and positive. While these studies uncover some differences between GenAI- and human-generated content, they do not explain how objective parameters influence human subjective perception. Our preliminary analysis seems to show that increasing the temperature causes ChatGPT-3 to generate more verbose output, even when the model is constrained to produce a maximum number of tokens. In the context of idea generation, verbose ideas have been observed to receive better evaluations (Kornish & Jones, 2021). This verbosity effect potentially extends to evaluations of message persuasiveness. As such, we call for future research to investigate the theoretical mechanisms linking objective LLM parameters to subjective perceptions. Additionally, gaining a deeper understanding of why these parameters influence persuasiveness in different ways could provide insights with respect to consumer heterogeneity. Thus, we propose the following two research questions:

**RQ** What are the theoretical mechanisms through which objective LLM parameters influence subjective perceptions?

**RQ** What theoretical constructs cause heterogeneity in consumer responses to variations of objective LLM parameters?

At the firm level, understanding the psychological mechanisms that link objective LLM parameters to persuasiveness, can help firms tailor messages to increase their customer base's purchase intention by defining message parameters ex-ante. Furthermore, since the marketing field has transitioned from transactional to relationship marketing (Morgan & Hunt, 1994) and further still to customer-engagement marketing (Blut et al., 2023; Harmeling et al., 2017; Pansari & Kumar, 2017), marketers today have a plethora of goals to pursue, all of which extend well beyond mere purchase. It is hence important to account for such heterogeneity of marketing performance metrics when assessing GenAI's capacity to craft persuasive messages.

To date, the computer science community has devoted much effort to developing prompt strategies aimed at improving LLMs' performance in analytical tasks. We present a summary of the most relevant strategies in Table 3. Marketing research is needed to investigate and propose innovative prompt strategies that can not only augment LLMs' efficacy in analytical tasks but also do likewise in various relevant marketing endeavors, such as empathy (Huang & Rust, 2021), recovering from negative events like product recalls (Raithel et al., 2023), or convincing consumers to adopt socially-relevant behavior (Winterich et al., 2023). Thus, we propose the following research questions:

**RQ** How can firms vary LLM parameters to create more persuasive messages?

**RQ** Which LLM parameter is most conducive to different marketing goals?

## Disclosing

Consumers appear to struggle in distinguishing GenAI-generated content from human- generated content (Jakesch et al., 2023). However, several governments (e.g., the U.S. and its AI Disclosure Act) and social platforms (e.g., TikTok, YouTube) are increasingly enforcing clear disclosure of AI-generated content. Therefore, research is warranted to explore the implications of such disclosure requirements for both consumers and firms.

At the consumer level, a growing body of marketing studies has focused on consumer responses to AI, such as robots (Mende et al., 2019), chatbots (Luo et al., 2019), or applications in medicine (Longoni et al., 2019). This research has unveiled the phenomenon of *algorithm aversion*, wherein humans tend to distrust and reject algorithms, even when

**Table 3** Overview of the main prompt strategies

| Strategy | Definition | Example |
|---|---|---|
| Zero-shot | Simply ask the model to do something | Please generate a new social media post about our latest product |
| Few-shot (Sewon et al., 2022) | Provide demonstrations in the prompt | This is awful! // Negative<br>The game was horrible! // Negative What a great day ! // … |
| Chain-of-thought (CoT) (Wei et al., 2022) | Provide explanation of the reasoning to get to the outcome | Q: Roger has 5 tennis balls. He buys 2 more cans of tennis balls. How many tennis balls does he have now?<br>A: Roger started with 5 balls 2 cans of 3 tennis balls each is 6 tennis balls. 5 + 6 = 11. The answer is 11<br>Q: The cafeteria had 23 apples. If they used 20 to make lunch and bought 6 more, how many apples do they have now? |
| Zero-shot CoT (Kojima et al., 2022) | Add the magic sentence: Let's think step by step | Q: Roger has 5 tennis balls. He buys 2 more cans of tennis balls. How many tennis balls does he have now?<br>A: Let's think step by step |

they outperform humans (Dietvorst et al., 2015). These studies have identified factors such as uniqueness neglect (Longoni et al., 2019), perceived lower empathy (Luo et al., 2019), and cost-cutting motives (Castelo et al., 2023) as drivers of consumers' reluctance to adopt AI applications. This research has also identified contextual conditions that seem to mitigate algorithm aversion: consumers are more inclined to trust algorithms for tasks perceived as objective (Castelo et al., 2019; Longoni et al., 2019) and in contexts with low identity relevance, such as numerical estimation or forecasting tasks (Logg et al., 2019). Conversely, aversion is exacerbated when AI performs tasks that consumers deem central to their identity, thus invoking self-enhancing and self-protective biases (Morewedge, 2022; Leung et al., 2018).

Given this context, consumer responses to a firm's disclosure of GenAI use appear ambiguous. On the one hand, GenAI demonstrates superior capabilities in generating empathy and unique content that is specifically tailored to consumer needs, compared to other types of AI (Huang & Rust, 2023). Therefore, algorithm aversion should theoretically be lower for GenAI than for other AI applications. On the other hand, creating novel content is a subjective task and creativity is widely regarded as a quintessential human capability (Koivisto & Grassini, 2023). Thus, prior studies suggest a negative response towards GenAI use (Castelo et al., 2019; Morewedge, 2022). In light of such conflicting predictions emerging from the literature, further research is needed to investigate consumer responses to a firm's use of GenAI and how the disclosure of GenAI-generated content differs from that generated by other types of AI.

Additionally, anecdotal evidence seems to suggest that disclosing GenAI use triggers new considerations for consumers, beyond those typically described in the algorithm aversion literature. For instance, when Levi's announced its decision to use GenAI to create models of more diverse body types and skin tones, the company faced strong criticism from consumers who feared that this decision would 'deprive people of opportunities'[5]. Thus, future research should investigate whether novel theoretical mechanisms drive consumer responses to the disclosure of GenAI-generated content, beyond those that influence consumer responses to the disclosure of other types of AI. Hence, we propose the following research questions:

**RQ** Do consumers respond differently to the disclosure of GenAI compared to the disclosure of other types of AI? What novel theoretical mechanisms explain consumer responses to a firm's disclosure of GenAI-generated content?

At the firm level, there is a need for research to explore how firms can effectively balance the benefits of GenAI use with potential negative consumer reactions to such use, particularly in light of increasing enforcement of disclosure by governments or social platforms. As the literature that explores how firms can mitigate algorithm aversion tends to analyze either consumer characteristics (Longoni et al., 2019; Luo et al., 2019) or task characteristics (Castelo et al., 2019; Morewedge, 2022), we advocate for future research on the role that brand associations (i.e., beliefs that consumers associate with a brand) play in mitigating or amplifying the effect of GenAI disclosure on brand equity. For instance, in terms of brand innovativeness (Brown & Dacin, 1997), two reactions are equally plausible theoretically. On the one hand, disclosing GenAI use might help amplify consumer perceptions of a firm's innovativeness. On the other hand, consumers might perceive inconsistency between a firm's self-described innovative image and that firm's use of GenAI to enhance internal creativity. Such a contrasting effect might amplify the negative effect of disclosing GenAI use for innovative firms (Brown & Dacin, 1997). Brand innovativeness serves as just one example, and future research is needed to investigate the moderating effect of this disclosure and other brand associations, including brand authenticity (Moulard et al., 2021) or corporate social responsibility. Thus, we propose the following research question:

**RQ** Which brand associations amplify the negative effect of GenAI disclosure on brand equity? Which associations mitigate this effect?

Further, research has investigated ways to mitigate negative reactions to a firm's use of AI, such as postponing disclosure time (Luo et al., 2019), framing AI as assisting rather than replacing humans (Longoni et al., 2019), reframing tasks as relatively objective (Castelo et al., 2019), and emphasizing the salience of utilitarian attributes (Longoni & Cian, 2022). We call for future research to investigate how firms can align their disclosure messages with their brand associations. For instance, underdog brands (Paharia et al., 2011) could frame the use of GenAI as a strategy for leveling the playing field, while innovative brands could frame their GenAI use as a demonstration of the firm's commitment to cutting-edge technology adoption. Hence, we propose the following research question:

**RQ** How can firms align disclosure messages to their firms' brand associations in order to mitigate the potential negative effect of disclosing GenAI use?

[5] https://www.independent.co.uk/life-style/fashion/levis-ai-models-diversity-backlash-b2310280.html

## Engaging

After consumers buy a firm's offering, it is important to maintain their engagement beyond mere transactions (Pansari & Kumar, 2017). Customer engagement marketing represents "the firm's deliberate effort to motivate, empower, and measure a customer's voluntary contribution to its marketing functions, beyond a core, economic transaction" (Harmeling et al., 2017, p.312). Among various initiatives aimed at enhancing customer engagement (CE), a recent meta-analysis reveals that task-based initiatives are particularly effective (Blut et al., 2023). These initiatives "deliberately exist to push customers' resource contributions" (Blut et al., 2023, p.497). Moreover, Harmeling et al. (2017) identify four key resources that consumers can voluntarily contribute to the firm's marketing function, including *creativity*.

We argue that GenAI and its use have implications for both consumers and firms. At the consumer level, an individual's ability to participate in task-based customer engagement (CE) initiatives is often limited by her own creativity and skills. GenAI can alleviate this constraint as consumers can employ different tools such as Midjourney or Stable Diffusion[6] to augment their limited creativity. For instance,

Coca-Cola partnered with OpenAI to launch the Real Magic platform, which enables users to generate original images cards using GPT-4, DALL·E, and historical pictures from Coca-Cola's archives. Winners of the competition had their work featured on Coca-Cola's digital billboards in prominent locations like New York's Times Square and London's Piccadilly Circus. By leveraging GenAI, even users with minimal graphic design skills could participate in Coca-Cola's initiative. However, the marketing literature suggests that customer engagement stems from the mental effort customers exert to create something novel, which fosters a sense of psychological ownership (Blut et al., 2023). In the absence of this sense of ownership, GenAI may potentially have a negative effect on customer engagement. Therefore, future research is essential to investigate the net effect of employing GenAI-based tools on customer engagement. Specifically, research should investigate the optimal level of GenAI use from the consumer's perspective, so firms may enhance creativity while preserving a sense of ownership among consumers, ultimately promoting sustained customer engagement. Accordingly, we propose the following research question:

**RQ** What are the consequences of employing GenAI-based tools for consumers working on customer engagement initiatives?

At the firm level, GenAI opens up brand new opportunities for firms to engage consumers by reducing the cognitive resources consumers need to participate fully in task-based CE initiatives. Firms adopt CE initiatives to access various customer resources beyond creativity, including customer network assets, persuasion capital, and knowledge stores (Harmeling et al., 2017). With GenAI eliminating the constraint for consumers to allocate creative resources, firms can engage even those consumers with lower levels of creativity. Thus, the potential risk of individual consumers experiencing lower psychological ownership in GenAI-driven CE initiatives may be counterbalanced by the chance for firms to reach a broader audience and access more relevant resources. Hence, there is a need for research on how firms can devise innovative CE initiatives leveraging GenAI. Specifically, future research could explore how firms can navigate the trade-off between the potential risk of generating lower individual CE and the advantages of accessing a broader consumer base. Hence, we propose the following research questions:

**RQ** What novel, task-based customer engagement strategies can firms pursue using GenAI?

**RQ** How can firms manage the trade-off between wider reach and lower psychological ownership in GenAI, task-based CE initiatives?

## Impact of GenAI for firms and consumers

Our previous discussion highlights both the opportunities and threats for firms that use GenAI in their innovation process. We expect that as more and more firms and consumers use GenAI, their capabilities will undergo significant changes. Our conversations with top executives across various industries reveal that this is a major concern. Some of the concerns expressed include: "The number one question that everyone is asking is: What can we (marketing) contribute to firm value in the future?" or "How can we convince the boardroom that there is still need for a marketing department? They have always viewed marketing as a cost and now they have the opportunity to reduce that cost. What value can we provide?". These concerns reflect a broader apprehension among executives regarding the evolving role of marketing in an era increasingly influenced by GenAI.

To address these concerns, we propose research questions that explore the effects of employing GenAI on: (1) the relationship between market-based assets and firm value; and (2) consumer skills, preferences, and role in the marketing processes. We summarize our research questions in Table 4.

[6] Midjourney and Stable Diffusion are text-to-image tools that allow users to create images of new objects from text prompts.

## The post-GenAI firm: How can marketing contribute to firm value?

Our previous discussion suggests that GenAI has the potential to fundamentally transform the value of key marketing capabilities, spanning from new product development to market information management to communication (Vorhies & Morgan, 2005). Hence, GenAI could redefine the essence of marketing's contribution to a firm's sustainable competitive advantage.

Firms create value for shareholders by leveraging market-based assets (Srivastava et al., 1998). These key assets, whether capabilities or resources, stem from interactions with customers (Srivastava et al., 1998; Slotegraaf et al., 2003). Our previous discussion highlights how this technology reshapes interactions between firm and customers throughout the innovation process. Similarly, Huang and Rust (2023) show that GenAI changes firm-customer interactions along the customer care journey. Thus, it is reasonable to anticipate that the repeated use of GenAI by firms in their innovation and caring processes will fundamentally reshape the market-based assets available to them. For instance, we discussed earlier the potential effect of disclosing GenAI use on a key relational asset such as brand equity. As another example, the reduced reliance on consumers to conduct market research might impede the accumulation of customer knowledge, which serves as a key intellectual market-based asset. Thus, future research is needed to investigate the following question:

**RQ** How does the use of GenAI alter the development and evolution of relational and intellectual market-based assets?

Second, for a market-based asset to confer a sustainable competitive advantage, it must be convertible, rare, inimitable, and non-substitutable (Srivastava et al., 1998). Theoretically, we envision two possible effects of GenAI on market-based assets. On the one hand, the ability to generate numerous messages or new product ideas at minimal cost within minutes greatly diminishes the value of key marketing capabilities (e.g., communication, new product development), making them more susceptible to imitation and less rare. On the other hand, a unique aspect of GenAI is that its output depends on the input that users provide, suggesting a complementary relationship with key market-based assets. For instance, GenAI creates new content based on its world knowledge at the time of training. As of January 2024, the latest knowledge available to some ChatGPT models dates back September 2023. This limitation could severely hinder GenAI's ability to produce valuable output in supporting new product development, given the frequent shifts in consumer preferences. Firms can curb the risk of creating something misaligned with current customer needs by ensuring they have up-to-date market knowledge to feed GenAI. From this perspective, GenAI necessitates complementary market-based assets to realize its full potential.

Initial empirical evidence in the literature is mixed. On the one hand, research supports a complementary view, as both Reisenbichler et al. (2022) and Reisenbichler et al. (2023) show that GenAI alone is insufficient; instead, adopting a "human-in-the-loop" approach is necessary. On the other hand, Girotra et al. (2023) find that ChatGPT-4 does not require humans to generate more and better ideas than MBA students. Thus, we conclude that the "jury is still out," underscoring the need for future research to investigate the boundary conditions of the relationship between GenAI, marketing capabilities, and firm value.

Marketing theory suggests that whether firms will use GenAI to substitute or complement marketing depends on the competitive advantage strategy that a firm pursues, as this strategy directly influences the role of marketing in the organization (McAlister et al., 2023). For firms that pursue a cost-leadership strategy, marketing is typically viewed as a staff function with no authority on marketing decisions; it is likely that such firms will view GenAI as an opportunity to reduce marketing costs. Even if GenAI were only capable of producing synthetic content comparable to human-generated content, its ability to create such content at nearly zero marginal cost is noteworthy. For instance, Reisenbichler et al. (2022) demonstrate that LLMs can achieve 91% cost saving in generating text-based SEO content. In these organizations, we anticipate that marketing will limit itself to the use of off-the-shelf GenAI solutions. For firms that adopt a differentiation strategy, marketing can take on either a staff function role with control over brand image and communications only, or a line function role that is responsible for delivering business results (McAlister et al., 2023). In the latter case, we expect marketing to play a more prominent role in the firm's GenAI use. For instance, marketing might be directly involved in fine-tuning GenAI foundational

**Table 4** The consequences of using GenAI

| Level of analysis | Research questions |
|---|---|
| Firm | • How does the use of GenAI alter the development and evolution of relational and intellectual market-based assets? |
| | • How does the use of GenAI in marketing activities vary across different marketing organizations? |
| Consumer | • How will GenAI change consumer preferences? |
| | • What is the new role of the post-GenAI consumer in the marketing procsses? |

models. In sum, future research is needed to investigate the following questions:

**RQ** How does the use of GenAI in marketing activities vary across different marketing organizations?

**RQ** How will GenAI change consumer preferences?

### The post-GenAI consumer: What role?

Given the described changes in consumer and firm behavior, we conclude our roadmap of future research by offering an initial portrayal of the post-GenAI consumer and by presenting research questions regarding the role of this emerging customer in future marketing processes.

The marketing field has recognized that new technologies often alter consumer behavior (Giebelhausen et al., 2014; Hoffman & Novak, 2018). Taking this idea a step further, neuroscientists and cognitive scientists warn that delegating human cognitive abilities to technologies could lead to permanent changes in our brain structure and fundamentally alter the cognitive abilities that govern human behavior (Fajnerová et al., 2018). For instance, relying on GPS for navigation reduces hippocampus functioning and related orientation skills (McKinlay, 2016), the invention of the printing press made mnemonic capabilities and the use of rhetoric for memorization obsolete (Eisenstein, 1979), and the use of smartphones is linked to shorter attention spans (Wilmer et al., 2017). Accordingly, we argue that research at the intersection of marketing, neuroscience, and cognition should investigate how GenAI will affect the cognitive capabilities of consumers, especially with respect to creativity.

Creativity is an integral part of consumers' daily life (Moreau & Dahl, 2005). Contrary to the idea of the creative genius, the cognitive literature suggests that every individual has the potential for creativity. More frequent involvement in creative cognitive processes enhances the likelihood of generating creative ideas (Ward, 2001). GenAI applications have been available to the general public for approximately 19 months, so it is premature to observe any significant changes. However, we anticipate that as more individuals integrate GenAI applications into their daily routines, humans may become less involved in the cognitive processes responsible for creativity. Similar to the impact of GPS on orientation skills (Fajnerová et al., 2018), an over-reliance on GenAI for generating novel content could potentially diminish consumers' appreciation for creativity. Research is hence necessary to investigate what customers with lower levels of creativity will value. For instance, will they still value innovation as much as current consumers do? In sum, we propose the following research question:

Finally, it is worth noting that the marketing literature has evolved in its conceptualization of the customer's role: from being seen as the target of a firm's offering, to being viewed as the object of orientation (Narver & Slater, 1990), and eventually to being recognized as a co-creator and co-producer (Prahalad & Ramaswamy, 2004). As we discussed in the co-ideation section, consumers' role as co-creators may become less relevant, especially if both consumers and employees rely on the same GenAI input for their creative output. This shift, combined with the changes in consumer's cognitive abilities and preferences previously discussed, presents an opportunity for future research about the new role that the post-GenAI consumer may assume in the marketing processes:

**RQ** What is the new role of the post-GenAI consumer in marketing processes?

## Conclusion

This paper analyzes the latest type of artificial intelligence, GenAI, and focuses on its capacity to create novel content. We propose a roadmap of future research in two main areas. First, we propose research that explores (a) how GenAI could alter consumer creative behavior, and (b) how firms consequently must re-adapt their strategies to fully harness the innovative potential of GenAI throughout the innovation process. Second, we propose research that analyzes the consequences of using GenAI for how marketing can contribute to firm value, as well as consequences with respect to consumer preferences, skills, and role in the marketing processes. We have chosen to focus our research roadmap on innovation, which represents one of the novel elements of GenAI compared to mechanical and thinking AI (Huang & Rust, 2021). We conclude this paper by sketching three further areas of potential interest for marketing research on GenAI: privacy, disinformation, and contribution of marketing to GenAI research.

Previously, we discussed the technical feasibility of fine-tuning existing foundational models with a firm's proprietary data, thus enabling firms to grasp the unique characteristics of a brand's image and customer base. However, sharing proprietary data for fine-tuning raises privacy concerns (Huang & Rust, 2023). While the marketing literature has primarily focused on consumer concerns regarding data privacy (Martin & Murphy, 2017; Martin et al., 2017; Thomaz et al., 2020), we highlight a major concern for firms: sharing proprietary knowledge poses the risk of diminishing the scarcity of a firm's market-based assets, potentially compromising its ability to sustain a competitive advantage. Thus, we call for future research that takes the firm perspective in order to investigate: (1) how firms can balance the advantage of supplementing their proprietary data to fully harness GenAI potential with the need to protect the sources of their competitive advantage, and (2) which firms can benefit the most from fine-tuning as well as which firms should instead exercise caution in doing so.

Second, the ability of GenAI to rapidly produce variations of the same content en masse and at negligible cost opens the floodgates to disinformation and diffusion of conspiracy theories. Traditionally, these topics have been considered a public policy issue, as political topics were the main target of these campaigns. The limited marketing research on this topic has mostly focused on providing psychological theories to explain the diffusion of conspiracy theories (Diaz Ruiz & Nilsson, 2023) or strategies to safeguard against it (Johar, 2022). However, anecdotal evidence suggests the rise of coordinated disinformation campaigns, orchestrated by ideologically motivated actors, to intentionally damage brands that take certain political stances or to favor national brands at the expense of multinationals. This has been observed, for instance, in media campaigns against Western Covid vaccines,[7] Starbucks,[8] and H&M (Sohn, 2021). GenAI will likely increase the frequency and scope of similar types of attacks against brands, making it a relevant topic for marketers as well. Against this background, we call for future research to: (1) quantify the impact of these orchestrated disinformation campaigns on brand equity, sales, and stock performance, and (2) investigate what mitigation strategies brands can adopt to nullify disinformation campaigns.

Finally, this manuscript offers a roadmap to conduct research about the likely contributions of GenAI to marketing. The opposite paradigm–which we call "Marketing for GenAI"–sounds equally promising. GenAI often operates like a black-box and even its creators have limited understanding of its cognitive nature. Fully harnessing the potential of GenAI requires a deeper understanding of the cognitive mechanisms through which it creates new content; this deeper understanding will help users better understand when GenAI is most likely to hallucinate, so they may develop strategies to reduce hallucination instances. Marketing has a rich tradition of decision making studies that investigate human cognitive biases (Dowling et al., 2020). Such knowledge can be fruitfully applied to gain rich insights on GenAI cognition (Binz and Schulz, 2023). Further, harnessing the full potential of GenAI requires proper prompting (Huang & Rust, 2023). Research indicates that LLMs are susceptible to technical biases, such as majority label bias (i.e., the model produces content that frequently appears in the prompt), recency bias (i.e., the model produces context appearing near the end of the prompt), and availability bias (i.e., the model prefers answers that are frequent in its pre-training data) (Zhao et al., 2021). Given the marketing field's history of developing strategies to mitigate human biases in surveys (Hulland et al., 2018), we call for research to explore how these strategies could be adapted to calibrate prompts and enhance the quality of GenAI output.

[7] https://shorturl.at/xH169.

[8] https://www.nbcnews.com/business/business-news/trolls-spread-hateful-fake-starbucks-coupon-n867501.

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