ORIGINAL EMPIRICAL RESEARCH

How generative AI Is shaping the future of marketing

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Abstract

Generative AI (Gen AI) is shaping the future of marketing. In the next decade, Gen AI will influence how marketers interact and communicate with customers, help create and deliver marketing content (text, images, and video), and inform methods for researching and developing new products and services. In both service and sales settings, Gen AI will affect customers directly and significantly. Therefore, marketers, researchers, and public policy makers require a clear understanding of Gen AI and its potential, as well as its limitations. To assist marketers in thinking through the adoption and implementation of Gen AI, the current article presents a four-quadrant organizing framework that highlights trade-offs in both the nature of Gen AI inputs and the extent of human augmentation needed to deliver Gen AI–generated outputs. This framework provides guidance for the selection and implementation of Gen AI tools, as well as recommendations for further research.

Keywords Generative AI · Artificial intelligence · Human augmentation · Customization

Using deep-learning models (or algorithms), generative AI (Gen AI) creates new and novel output (e.g., text, image, video) from existing content. As such, Gen AI has substantially improved marketing outcomes across multiple domains. For example, leading companies use Gen AI to create suitable ad copy (Colburn, 2024): With Gen AI–created ad copy, Vanguard was able to increase conversion rates for its LinkedIn ads by 15%. Similarly, Emirates NBD bank (based in the UAE) relied on Gen AI to create personalized credit card offers that increased leads by 177%. Unilever also leveraged Gen AI in developing an application that crafts initial responses to customer messages by analyzing not only the issues that the customers raise, but also the sentiment underlying their messages. According to Unilever's chief information officer, its use of Gen AI has reduced the amount of time customer agents spend on responses by approximately 90% (Olavsrud, 2023). Walmart similarly used Gen AI to create a chatbot to execute marketing negotiations with vendors, most of which indicated that they preferred working with the chatbot, which also delivered 3% cost savings (Hoek et al., 2022). As these use cases illustrate, the impact of Gen AI is significant; it is estimated to exceed $1.3 trillion by 2032 due to its potential to disrupt and change multiple businesses (Bloomberg, 2023).

Herein, we aim to: (1) distinguish Generative AI (Gen AI) from other forms of AI while highlighting its benefits, (2) identify key considerations for practitioners when

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implementing Gen AI, and (3) explain potential negative consequences of strategic misalignment in the selection of Gen AI tools. The key contribution is a four-quadrant framework that helps select Gen AI tools based on input type and the level of human modification needed. Using this framework, we provide examples of Gen AI solutions, discuss trade-offs, offer implementation suggestions, and propose areas for future research.

The impact of Gen AI is rippling exponentially across domains and industries, driving the fast-paced evolution of perspectives and solutions. To capture this dynamic evolution and construct our framework, we gathered insights from recent relevant industry reports, interviews with industry experts, and a targeted review of pertinent literature. We partnered with researchers who developed a recent Amazon Web Service industry report (Davenport et al. 2023a), where they surveyed more than 300 chief data officers (CDOs) with respect to their Gen AI adoption. We learned that more than three-quarters of these surveyed CDOs believed that Gen AI would transform their business environments. Further, over half also planned to invest more in Gen AI. We further augment the insights from the survey data and qualitative interviews by Davenport et al. (2023a) with additional interviews with senior executives across functions and industries.

Our discussions reveal that many firms already are having conversations—both internally and with their customers and technology providers—about the variety of ways that Gen AI can help them serve their customers, compete in the marketplace, and improve their bottom lines. Yet the experimentation that the CDOs describe in the AWS survey mostly takes place at the individual employee level (50%)—only about 20% of them involve the overall organization. Such findings suggest a significant need for further scholarly guidance in this nascent, critical area of evolution in marketing practice and beyond. Our discussions also reveal some deep uncertainty. First, respondents continue to wrestle with the question of how to best to implement Gen AI. Their concerns include the best way to experiment with Gen AI, trade-offs between internal and external data, and the need for high quality data (though this need appears to vary across industries). Second, the executives consistently express ongoing concerns related to privacy and transparency, pertaining to both data input in Gen AI and created in collaboration with Gen AI. The popular press has echoed these concerns and suggested the need for human augmentation, to ensure the appropriateness of Gen AI output. In a recent opinion article for *Fast Company* for example, Jeff Puritt, CEO of TELUS International argues that the key questions include "how decision-makers can help to 'get GenAI right' [and keep] … humans in the loop …" (Puritt, 2023).

Considering its potential to catalyze novel, unprecedented marketing capabilities (Harkness et al., 2023), Gen AI adoption is likely to be especially prominent in marketing, media,

and consumer technology sectors—significantly more so than in legal services, insurance, or data analytics, for example (JP Morgan, 2024). As such, it seems fitting that members of the marketing discipline take the lead on research into Gen AI.

Generative AI versus analytical AI

Distinguishing Gen AI from analytical AI

To define Gen AI, we compare it with analytical AI, which represents a classic, widely available form of AI that has been employed for decades. In terms of similarities, both *analytical AI* (also referred to as predictive AI or discriminative AI) and *generative AI* rely on statistical machine learning, a technique for training models on past data and using the models to make predictions. However, the two forms of AI have different objectives, employ different algorithm types, use different types of data, and generate different types of output.

Analytical AI attempts to analyze past data to predict future outcomes using structured (usually numerical) data. Most analytical AI algorithms employ variants of predictive models such as regression analysis, neural networks, causal forests, etc., and are relatively interpretable and explainable. For example, using prior data about customer purchases, analytical AI might infer what product each customer is likely to buy next or the price that the customer is likely to pay for a specific item. Spotify leverages analytical AI to suggest playlists that reflect some activity (e.g., having dinner) or motivation (e.g., discovery) expressed by users. Banks use analytical AI to classify customers into those more or less likely to default on loans. In an influential series of papers, Huang and Rust (2021) parse analytical AI into mechanical AI, thinking AI, and feeling AI, contingent on the kind of insights it generates, and outline the marketing tasks for which each AI is most suited (Huang & Rust, 2021, Table 1).

In short, analytical AI is what firms leverage to improve their large-scale operations, across various functions (Siegel, 2024). Accordingly, AI-driven predictions power millions of business decisions, including "whom to call, mail, approve, test, diagnose, warn, investigate, incarcerate, set up on a date or medicate" (Abdullahi, 2024). Such widespread applications in domains spanning advertising, marketing, customer service, sales, healthcare, peer-to-peer marketplaces, and fraud detection (Abdullahi, 2024; Satornino et al., 2023), together with illustrative use cases and illustrations presented in prior research (Davenport et al., 2020; Guha et al., 2021; Shankar, 2018), emphasize the capacity for substantial value creation. Such practices also have facilitated reductions in prediction costs (Agrawal et al., 2019).

Table 1 Analytical AI versus Gen AI

	Analytical AI	Generative AI
S-T-P	Predict -despite incomplete information- whether customer might be in target segment Predict long term customer value	Create first draft of marketing plan Critique marketing plan Create suitable positioning statements
4 Ps	Predict optimal price Predict best next-offer Predict optimal ad space & ad space price Predict customer mood during calls Predict best personalized offer	Create advertisements Create product descriptions Summarize customer reviews; generate insight Create social media posts
Marketing Research	Predict how long persons take to complete surveys Perform initial analysis of data	Create synthetic respondents for marketing research New product ideation Summarize qualitive interviews
Marketing-relevant functions	Predict fraudulent transactions Predict how likely products is to be returned	Create software code Improve software code
Sales	Predict which leads should be pursued	Create sales scripts Create counter to any sales proposal ("sparring partner")
Customer service	Predict complainer sentiment in real time	Create first draft of customer complaint replies Create post facto summaries/analyses customer complaints to identify recurring problem areas

Although Gen AI also uses some type of analytical AI as its underlying foundation, its predictions are textual in nature and it generates ***new content*** from past content, such as predictions about future content that are based on data inputs and existing content (using "attention" techniques, Vaswani et al., 2017) or training on sequential content data. The predicted content may be the next word in a sentence, the next component of an image, the next note in a song, or the next amino acid in a protein. These types of data are less structured and numerical in nature (though they typically get converted to numbers for use in Gen AI models). The algorithms include attention-oriented techniques, as well as very large and complex deep learning neural networks. (Notably, it is difficult or impossible to explain why a particular Gen AI outcome has been produced in response to a specific prompt.) In addition, Gen AI can operate across various domains and generate different forms of output, such as public relations content, social media posts, programming code, and unique images (Davenport & Mittal, 2022).

Once a Gen AI model has been trained on and systematically analyzed significant amounts of unstructured (typically, text or image) data, it can summarize that input, as well as produce novel insights based on the analysis (Davenport et al., 2023a, b). For example, while reviewing competitors' annual reports, Gen AI can identify information disclosures that hint at significant changes in competitors' corporate strategies. Gen AI output also pertains to mechanical, thinking, and feeling domains, such that it can be used for (1) simple, repetitive tasks, as when Amazon uses Gen AI to summarize reviews (Walk-Morris, 2023); (2) complex tasks, such as acting like a "sparring partner" who creates responses to solicitations during practice sales calls (Grewal et al., 2024a); or (3) emotional, communicative tasks, like creating a painting (Spair, 2024). As such, Gen AI has the potential to influence every element of the marketing strategy and every step of the strategic planning process.

The accuracy of both generative and analytical AI is largely contingent on the quality and quantity of training data, though the choice of algorithm also can have an impact. Well-trained analytical AI models can effectively identify a suitable response (e.g., next best offer) or classify objects (e.g., which loans are most likely to go delinquent). Generative AI language models trained on accurate data are more likely to produce accurate and useful textual outputs. However, many models rely on data from the internet, which feature a wide range of accuracy levels. Both Gen AI and analytical AI models also are probabilistic rather than deterministic. Thus, analytical AI models sometimes make incorrect predictions about whether a person will repay a loan or buy a product at a particular price. Similarly, Gen AI models have a well-known tendency to "hallucinate," or create inaccurate output (Vana et al., 2024). As Huang and Rust (2024) acknowledge, Gen AI is good at recognizing expressed emotions but may be prone to hallucinating responses. This trait is unavoidable, given the probabilistic nature of the models. Without dramatically different Gen AI models, organizations that adopt generative AI will continue to have to deal with the risk of inaccurate or inappropriate content predictions.

Table 1 compares analytical AI and Gen AI, across various marketing-relevant functions. There are clear points of similarity, in that both analytical AI and Gen AI can have impacts across the full marketing plan, from segmentation, targeting, and positioning; to selecting the marketing mix; to conducting marketing research; to sales and customer service (e.g., customer care, Huang & Rust, 2024); to related functions (e.g., coding, fraud detection). But we also note some critical

points of difference. The main purpose of analytical AI is to offer high-quality predictions, such as anticipating which offer is most likely to spark a consumer's interest (e.g., Stitchfix uses analytical AI to predict which clothing subscribers will enjoy; Davenport et al., 2020). In contrast, Gen AI creates new content, such as multiple versions of advertisements for a particular campaign (AIT News Desk, 2023).

There are two strategic decisions that firms must make when considering Gen AI solutions: the input into Gen AI: the input into Gen AI (e.g., on which data set should the Gen AI be trained or prompted?) and the Gen AI output deployment (e.g., should the newly created Gen AI content get shared directly, or should humans intervene prior to sharing?). First, the level of input customization is an important consideration. Currently, the most popular and widely used Gen AI solution, ChatGPT, uses general large language models (LLM) that span a wide variety of information as input. Conversely, Bloomberg GPT uses a custom data set of content that is specific to the finance sector (Davenport & Alavi, 2023). Between these two extremes lie firms like Morgan Stanley, which uses an LLM customization technique called "retrieval-augmented generation" (RAG) to tune its LLM with a curated set of internal documents (Davenport & Alavi, 2023). This approach involves augmenting a general LLM with customized content to tune its LLM with a curated set of internal documents (Gao et al., 2023). The documents are typically transformed into numeric form (e.g., "embeddings") and stored in a vector database so that they can be easily searched for relevance to a user prompt. One advantage of this approach is that it allows the LLM to present citations to specific documents in its responses. The selection of Gen AI input, along this continuum from general to custom inputs, represents the first major decision for firms seeking to implement Gen AI solutions.[1]

Second, it is also important to consider how much human (or programmed) augmentation is necessary before deploying Gen AI output. For example, some firms might deploy Chat-GPT 4.0 for communications with their employees and affiliates and provide the resulting responses with little or no human augmentation. Other firms instead might prefer Grammarly, a Gen AI–based writing assistant, for such purposes. Unlike ChatGPT, Grammarly offers some automated restrictions, such as intervening to suppress responses to offensive prompts. The BCG–Zeiss Gen AI solution (BCG, 2024) typically provides responses to optometry practice managers only, which then can be forwarded to patients (i.e., customers), after careful review. The practice manager thus serves as a (human) intermediary that augments the output by vetting it for accuracy—despite

claims that more than 90% of BCG–Zeiss Gen AI responses are "patient-ready" (BCG, 2024). Like the customization of the inputs, the level of human augmentation varies along a continuum, from none to automatic restrictions (e.g., Grammarly), to human augmentation (e.g. BCG-Zeiss), creating another critical decision for the firm.

Firm perspectives on analytical and generative AI

Analytical AI has had, and is likely to continue to have, substantial impacts across enterprise functions (e.g., Davenport & Mittal, 2023; Davenport et al., 2020; Mahurkar, 2023). Thus far, it tends to be more accurate and reliable than newly developed Gen AI applications, as well as more robust to outliers and noise. It is trained on a company's own structured numerical data, so it offers more proprietary benefits to the company that created it. Although both analytical AI and Gen AI are somewhat opaque, the models for the former tend to be easier to interpret (Mahurkar, 2023), such that it is relatively easier to understand how analytical AI models make predictions—a critical issue for firms that must justify the AI models they use for customer segmentation, price setting, or classifying a transaction as fraudulent. Further, although Gen AI sparks excitement due to its impressive potential, analytical AI has done more (thus far) to enhance business performance and efficiencies (Siegel, 2024), such that analytical AI continues to be the primary format being adopted in practice (Mahurkar, 2023).

Notwithstanding the advantages of analytical AI, the appeal of Gen AI remains compelling for several reasons. First, unlike analytical AI, (some) Gen AI solutions can be implemented immediately, irrespective of a company's own data structure. Consider the case of a large Asian bank, which previously had its call center agents manually record the customer service issues. Now, the bank uses an internally-developed Gen AI application to transcribe (and if needed, summarize) the customer service call, and search the bank's knowledge base to retrieve information relevant to the customer query. Based on data collected, call handling time has been reduced by nearly 20%, so call center agents can spend more time interfacing with customers (Lim, 2024).

Second, analytical AI often requires the input data to be formatted in a certain way, with some certain level of quality, such that small and poorly resourced firms might lack the internal data needed to implement analytical AI models. In contrast, small and poorly resourced firms can readily take advantage of Gen AI, such as by assigning ChatGPT to create drafts of social media posts, check code, or create sales scripts (Guha et al., 2023). Even if Gen AI can benefit from high-quality proprietary data too (Davenport & Tiwari, 2024; Earley & Bernhoff, 2020), in the absence of such data, Gen AI solutions like ChatGPT and Grammarly still provide means for value creation.

Third, the capabilities of Gen AI continue to advance very rapidly. As Fig. 1 shows, ChatGPT 4 achieved a significant

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[1] For this article, we largely refer to LLMs, which are Gen AI models trained on large data sets with primarily text.

data (e.g., Bard, ChatGPT), but we also acknowledge that Gen AI encompasses multimodal data, such as large.

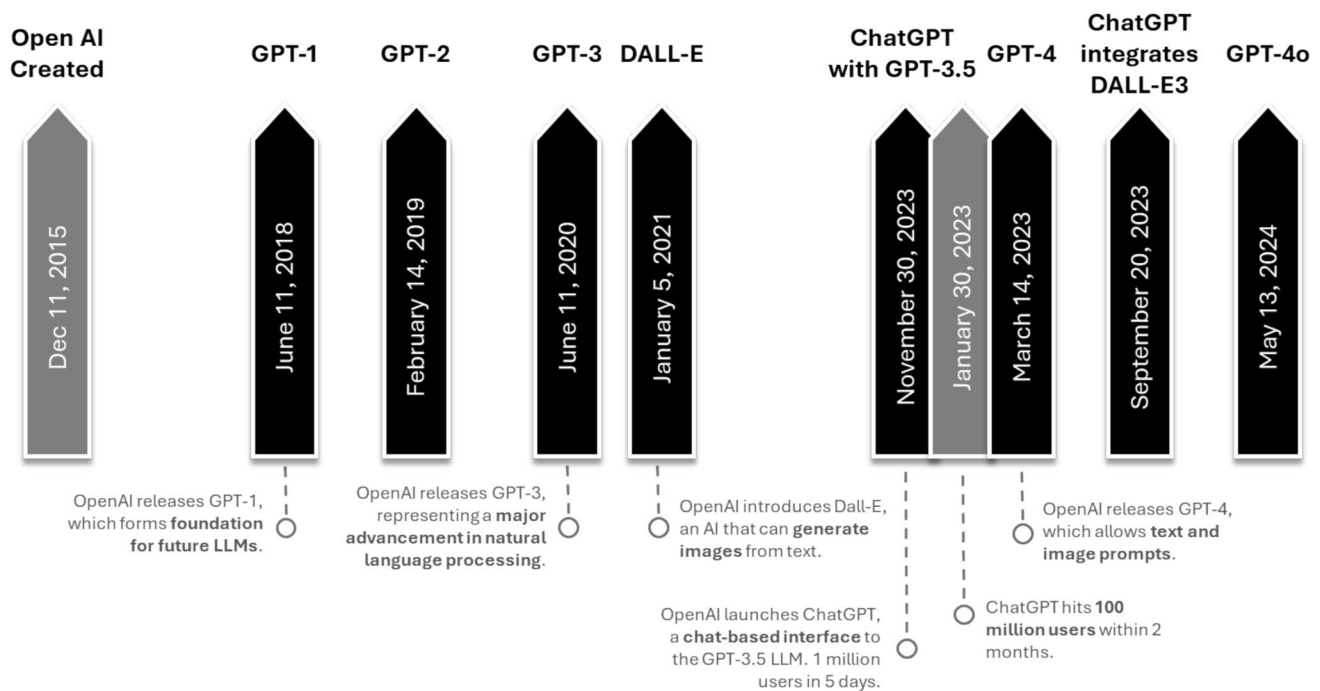vision models (LVMs), including Dino or Clip.

Fig. 1 History of ChatGPT (adapted from Malik, 2023)

increase in capability compared with ChatGPT 3.5. It can generate text output that looks like social media posts, along with photos and images that might appear in advertising campaigns (Rogers, 2024). The latter capacity is a substantial advance, even though the latest version launched less than four months after Chat GPT 3.5. Many other Gen AI models exhibit similar levels of progress in a short time.

Consider an illustrative example to understand these three relevant benefits (Grewal et al., 2024a). Suppose a marketing agency is tasked with creating a digital marketing campaign for a major beverage producer, establishing a tie-in with a major sporting event such as the Olympics or FIFA World Cup. The marketer would expect to select the appropriate sporting event, determine an appropriate and coherent marketing message, create images for social media posts, and create corresponding content that is appropriate to post on various social media platforms. Performing these tasks manually would take months of significant effort.

However, if the marketer chose to use Gen AI, this campaign development could be completed in days or weeks. Specifically, the marketer would first select the appropriate AI tool (e.g., ChatGPT 4.0), then craft a prompt to solicit sporting events that might fit with the beverage producer's brand. After identifying an event of interest, the marketer can craft another ChatGPT 4.0 prompt that is likely to create marketing messages that attract the target audience at the selected event, are consistent with the brand positioning, and match the scope and platforms the marketer intends to use for the marketing campaign.

The marketer also might prompt ChatGPT 4.0 to provide a description of images that might correspond with the selected messages. With this output, the marketer could turn to an image generator (e.g., OpenAI's DALL-E) and provide it with the image description provided by ChatGPT 4.0, leading to the creation of an image that corresponds with the selected marketing messages. Finally, the marketer can prompt ChatGPT 4.0 to provide customized messages for different social media platforms.

Following an internal review for accuracy and appropriateness, the marketer can deliver all these items and ideas to the client, for relatively minimal monetary and time costs. This example illustrates the potential benefits to marketers, which reflect rapid advances in Gen AI. To specify these benefits in greater detail, we integrate our survey insights and interviews with senior managers with the results of a careful literature review.

Understanding generative AI

Insights from practice

In exploratory discussions with senior executives,[2] we gathered information about how their firms and their customers use Gen AI, as well as which factors they consider when

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[2] In addition to the interviews conducted as part of the CDO survey (Davenport et al. 2023a, 2024), we interviewed 10 other senior executives, from a mix of small and large organizations that are exploring and implementing gen AI applications.

implementing Gen AI solutions. In Table 2, we present a sample of perspectives from these interactions, focusing on (1) the benefits of Gen AI, (2) how to implement Gen AI, and (3) concerns about Gen AI. As might be expected, these senior managers outlined the many benefits of Gen AI, including revenue impacts, cost reductions, and ease of deployment. They also noted the need to consider their strategic choices and concerns carefully. In these discussions, we identified two key considerations: the choice between using a general or custom input data set and the degree of human augmentation to deploy.

Gen AI solution involving a general data set

As a typical Gen AI solution, ChatGPT can offer benefits in multiple domains. This LLM (GPT-3.5 or GPT-4) is based on a general data set, which means that it leverages large quantities of publicly available data that provide a broad scope of source material for creating novel output. Therefore, ChatGPT could be used to create novel social media content and generate unique services or sales scripts (Sinha et al., 2023) based on a large body of unstructured information.

In our discussions, the CEO of a technology start-up highlighted the use of Gen AI by both the marketing and technology departments. Specifically, the marketing department leveraged ChatGPT to craft new social media content, substantially improving productivity. These substantial time savings effectively lowered the firm's costs, while simultaneously providing novel content. The benefits are immediately clear in the CEO's description of their first attempts at using ChatGPT, as are the limitations of the output:

"So then what we did was we said… let's try this Chat-GPT thing…. we did …brainstorming….kind of put it to ChatGPT and said… 'Hey, write us a blog'. And it wrote us a beautiful blog….this is better than what … external people write….we …[need to] fix the things that were wrong…"

Regarding the technology and new product development departments, the CEO shared that they had achieved substantial savings from using ChatGPT. Due to the broad scope of information from which the general data set underpinning ChatGPT can draw, the use of this Gen AI tool substantially augmented human programming efforts, leading to a reduction in employee headcount and increased productivity. Specifically, it reduced staffing needs, because the company only required two software teams instead of three, which yielded substantial, quantifiable cost savings:

"we had planned on having three distinct engineering squads… through ChatGPT, we can get our roadmap done with one less squad… that [is] huge"

These savings and benefits would be difficult and costly to achieve if the Gen AI tool required a custom data set. However, the CEO also identified some trade-offs in the decision to adopt the general LLM, including privacy concerns. This informant admitted that the company was unsure if everything uploaded onto ChatGPT would remain private or be used as input in responding to others' prompts. As a safeguard against privacy breaches, the technology teams uploaded only a subsection of code onto ChatGPT, not the firm's full code library. Executives asserted that even if recent ChatGPT promise of privacy, this concern is likely to persist.

Gen AI solution involving a custom data set

In cases where the consequences of inadvertently releasing sensitive information using a general Gen AI tool such as ChatGPT are high, custom input may be preferred. In contrast to the broad scope of general inputs, Gen AI models involving custom data sets contain information that is (1) firm-specific (not generally available in the public sphere), (2) constantly updated, and (3) generally reliable. Although more costly and difficult to deploy, when the risks and trade-offs of general data set–based solutions are too great, deploying a Gen AI solution based on custom inputs may be more appropriate.

As an example of an appropriate use of custom inputs, during our discussion with a retail technology vendor, they disclosed that they were creating a Gen AI solution for a specific retailer designed to provide patrons with the location of any product in the store, as well as information about specific stockkeeping units (SKU). In the case of a stockout, it would offer information about replacement timetables and potential substitutes. It also might suggest complementary items and (down the road) offer price promotions, depending on customer and other factors. All of these features required store-specific information, so this Gen AI solution utilized a custom data set. The vendor further clarified two types of benefits obtained from using custom LLMs.

First, because the output from the Gen AI solution was store-specific, it helped mitigate demands on retail workers during peak times. This retailer earned substantial sales through shopping agents, such as those working for Instacart. These Instacart shoppers—under significant time pressure to assemble and deliver products to offsite customers—often would demand considerable time and assistance from the store employees during peak shopping times (when retail store employees should be focused on in-store customers):

"it's incredibly oppressive…. [Instacart shoppers would] have a list of 20 things, and they would just go up to a store employee [and ask] where are the canned onions? Where's this? Where is that?... [we are now] seeing some efficiencies in offloading those [questions] to an app…"

Table 2 Senior executives' perspectives on developing and implementing Gen AI applications

Profile	Benefits of Gen AI	Concerns about Gen AI	Implementing Gen AI
EVP–Technology and Data, global marketing services company[1] Prior experience as partner in a major consulting firm	Gen AI enables rapid image creation for new marketing campaigns	Using LLMs (and LVMs) in ways that do not infringe on intellectual property	
Head of Sales, Edtech startup, with operations in North America and Europe[2]	Using Gen AI substantially improves productivity, in both education and business	Many are unwilling to use Gen AI, if materials uploaded might (potentially) shared with others, and/or if content co-created with Gen AI might (potentially) be shared with others	Including privacy as part of the Gen AI offering is valued by (many) customers
Chief Data Science Officer, large U.S. retailer[1]	Using Gen AI to create product labels	Use of Gen AI for product labeling generates hallucinations; editing them reduces productivity	
Chief Data and Analytics Officer, large Canadian bank[1]	Early Gen AI application for customer service; won award for best AI in practice	Key concerns about privacy, bias, and intellectual property rights infringement, "mostly related to privacy and related to bias. And now that there's so much, especially in the generative space, we're looking at patent law and copyrights and ownership."	Gen AI trained on customers' questions and answers
Chief Data Officer, large U.S. telecom firm[1]	Gen AI used for a wide variety of purposes across the company, including coding, data analysis, and image finding		"Boot camp" training to implement Gen AI across the organization
Chief Technology Officer, leading provider of research and ratings to asset management firms worldwide[1]	Gen AI created a financial Q&A system using the firm's in-house content		Gen AI capability was created quickly, with a relatively small budget
CEO of a technology start-up[2]	Using Gen AI reduced costs (time, headcount) for marketing (e.g., ad copy) and software development	Materials uploaded into Gen AI might be subsequently shared with others	
Advisor, Major retail chain[2]	Using Gen AI can increase revenue and streamline operations by freeing up resources		Benefits from both a general (e.g., generalized information like recipes) and custom, regularly updated (e.g., where certain items are located in the store) data sets
Former CMO, large private university[1]	Uses Gen AI to create ad copy and email copy, with both text and images	Beyond hallucinations, intellectual property rights infringement is a key risk	Gen AI output is reviewed by university employees; the cost of inappropriate or incorrect copy reaching external stakeholders is very high, "So everything that we do is more of a co pilot orientation, right? We don't just let it run."
Director of Marketing Communications, large U.S. think tank[2]	Gen AI can create initial drafts of emails and website content (both text and images), such that it is "good for initial drafts, saves time…."	Gen AI makes errors and also might use copyrighted content. Correcting for it is very concerning and important	

Table 2 (continued)

Profile	Benefits of Gen AI	Concerns about Gen AI	Implementing Gen AI
Chief Analytics Officer, global CPG company[1/a]	Uses Gen AI to collect consumer insights; mass personalization at scale (for ads); new product testing; and understanding consumer sentiment: "We are using generative AI for synthesizing consumer and shopper insights and other marketing use cases. We're talking with our marketing agencies about mass personalization at scale of ads or offers. And the other area is innovation. So new product development, perhaps some automated consumer insights, and then automated consumer testing with digital twins. We want to use it to understand consumer sentiment and what they're asking for. So those are the enterprise 'big bets'. …"		
Chief Analytics Officer, global media company[1/a]	Exploring Gen AI and associated use cases: "We're all very interested in generative AI. Clients and employees are experimenting within the guardrails that have been placed on them. And I expect that it will gather steam slowly and there'll eventually be some kind of tipping point. We'll suddenly realize, wow, this thing has had a tremendous impact."	Find ways to experiment with Gen AI, yet retain guardrails	
Chief Data Officer, global financial services company[1/a]		Creating clear, additional guidelines for Gen AI usage, for which purpose it engaged lawyers, data professionals, and human resource professionals	Questions about extent of use of proprietary data
Managing Director with responsibility for AI, global bank[1/a]		Not all Gen AI is "transparent" (both input data and algorithms)	Important to know which data the Gen AI uses; high quality (accurate, up-to-date) data are critical

[1]Large firm. [2]Small firm. [a]Interviews conducted for the CDO survey

By providing customized output (derived from information that is not publicly available) via the Gen AI solution to the Instacart shoppers, the retailer aimed to reduce the demands on retail store employees' time, with the hope it would translate into labor reductions and cost savings. These benefits could not be realized without the use of store-specific (e.g., product locations, prices) information that is both fresh (e.g., promotions) and reliable (e.g., stockouts).

Second, the Gen AI solution promised increased revenues. The retail store conducted a pilot field test and compared sales before versus after implementing the Gen AI solution. The test identified a substantial sales lift when the retailer implemented the Gen AI, specifically in "hard-to-shop" categories. Although field tests like these are subject to limitations, this initial, positive result was encouraging, and again, would not be possible without the use of in-store data that were updated regularly and reliable. This much more technically complex implementation, compared with using a general, publicly available data set, demands training and prompting the Gen AI model with firm-specific information, as well as integration with existing technology architectures and systems, including inventory management and pricing optimization systems. Many companies may find such efforts difficult or impossible to implement without considerable external assistance from vendors or consultants.

Human augmentation

Beyond the choice of general or custom input data sets, the preceding examples (i.e., technology start-up firm and retail technology vendor) illuminate another consideration: the extent of the need for human augmentation. Understanding how humans (human intelligence) and AI should collaborate is a critical topic, as highlighted by both Huang and Rust (2021) and Davenport et al. (2020). For our purposes, human augmentation refers to modifications of Gen AI output by a human actor, serving as a go-between the Gen AI solution and the end user.[3] For example, a senior manager in the digital marketing/SEO division of a national law firm explained that when developing social media content, ChatGPT can provide output to the firm's marketing department, which reviews that content for appropriateness and impact and edits it as needed, before disseminating the output. In this case, the Gen AI (ChatGPT) solution is *augmented* by the *human efforts* of the marketing personnel. In contrast, the vendor of the aforementioned retail Gen AI solution explicitly built its offering to *replace human effort* and communicate directly with retail customers, without

any human augmentation; the Gen AI output is delivered directly to end users (i.e., Instacart shoppers).

Due to the need for accuracy, many organizations require some human augmentation between the Gen AI solution and the final user. For example, a vice president at a *Fortune* 500 company described to us how the firm's sales teams employ a Gen AI solution to generate first drafts of sales proposals. Before sending the proposals to clients, however, the sales teams review drafts and customize the content to the specific client's needs, leveraging their nuanced understanding of each client's needs and objectives. The benefit of employing a Gen AI solution in this manner, according to this informant, is the efficiency of editing a baseline proposal, rather than starting from a blank page. It reduces both the financial cost and the time needed to produce a sales proposal. However, a key part of this process is a human review, which reduces the chance of unsuitable content and subsequent loss of sales, though it is slower than direct delivery of the content to users would be.

Another senior manager underscored the importance of human augmentation. This manager worked for a tech company that sells a Gen AI solution for proofreading and copyediting services, as well as an array of value-added services (e.g., document retrieval, brainstorming, structured learning solutions, writing in certain ways or using a certain tone to cater to specific audiences). As its key benefits, this Gen AI solution can improve writing quality and increase efficiency by reducing the time needed for writing, document retrieval, and brainstorming. It also promises strong privacy protection; any materials it helps create and all materials uploaded to the Gen AI remain wholly the property of the customer and will not be used or saved by the Gen AI solution provider. In addition, the Gen AI solution screens prompts and queries for "offensive content," to be reviewed later by an employee. This human augmentation, even if delayed, has strong appeal for educational institutions. Such screening might also help limit legal liabilities, were an individual user to employ the solution nefariously, such as to plan and execute an illegal act.

The key point emerging from this discussion is that firms implementing Gen AI solutions need to be concerned about the extent of human augmentation between Gen AI and the end customer. They should explicitly and carefully consider if the Gen AI output should go directly to an outside-the-firm customer or if there should be some form of (prior) human augmentation (e.g., employee overviews the Gen AI output) before that output gets disseminated to customers.

Insights from academia

Turning our attention to extant academic literature, we gather insights from scholars immersed in the theoretical and empirical exploration of Gen AI, who have considered its likely impacts on practice and scholarship. Despite the relative

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[3] Augmentation is not limited to Gen AI; Davenport et al. (2020) cite Stitch Fix, which augments data produced by analytical AI with human employees' efforts.

dearth of research on Gen AI in marketing literature, we can draw from related scholarly domains to extract insights that may be of use in the marketing domain. Prior literature resonates with the experiences of the practitioners we interviewed regarding the benefits of Gen AI, such as speed (i.e., increased efficiency), the ability to contribute to marketing tasks like marketing research (e.g., by creating synthetic data), and enhanced ideation (e.g., new products). Table 3 provides an overview of extant literature, with a summary of key insights.

Although the benefits related to efficiency are well supported by extant literature, the results regarding effectiveness are mixed. Many employees can be more effective using Gen AI, but the use of Gen AI also carries risks. For example, Gen AI can hallucinate (provide inaccurate or fabricated information; Cacicio & Riggs, 2023), which reduces its effectiveness. As such, some scholars recommend human augmentation, due to its capacity to increase both the job satisfaction of content producers and the effectiveness of Gen AI outputs (e.g., Zhang & Gosline, 2023). However, reviews require human time and attention, so such effort reduces the productivity benefits of Gen AI solutions.

Beyond Gen AI's propensity to hallucinate, scholars have highlighted other explicit concerns. First, the algorithms are opaque and difficult to explain, which can be a serious issue in cases where Gen AI produces unexpected or inappropriate output (Williams, 2024), for which the marketer may be held accountable. Second, its output can be biased (Piers, 2024), an issue that largely depends on the input training data in the model. For example, Grewal et al., (2024b) report instances of ChatGPT exhibiting a progressive bias. Third, privacy-related concerns are prevalent, though they are less common with customized versions of these models within companies. Fourth, we note concerns about ethics, including Gen AI using data that might have copyright protection (some of these considerations are being adjudicated in the courts, at the time of writing). Fifth, our review underscores the importance of regulatory, human, and process human augmentation to mitigate various risks.

Perhaps the most important insight we gleaned from this literature review is that there is currently little marketing-specific, empirically supported guidance for practitioners. We might carefully draw inferences from a broad multidisciplinary lens, but we also note a glaring lack of research into Gen AI as it pertains to the specific application concerns of marketers. Such a gap might not be surprising, considering how relatively new Gen AI technology is to the field at large. Yet marketing practitioners already are grappling with the nuances and trade-offs of deploying Gen AI solutions, emphasizing the dire need for rigorous scholarship. As is true of any novel, fast-developing field, we expect a plethora of papers to enter the review process soon, but the impact of Gen AI on the practice of marketing makes it critically important to focus scholarly attention in this space.

Developing a Gen AI organizing framework

To that end, we present an organizing framework, extrapolated from our review of both scholarly content and interviews with senior managers, designed to provide guidance for implementing Gen AI solutions, as well as illuminating inherent trade-offs. Specifically, we present important considerations for firms that plan to implement Gen AI solutions, organized around two key issues: the type of Gen AI input and the handling of Gen AI output. We follow the framework with a discussion of promising avenues for continued scholarly exploration.

Gen AI inputs

Different Gen AI solutions involve *custom* versus more *general* inputs (e.g., LLMs, LVMs). A custom Gen AI solution requires company-specific information, which may be supplemented with general information. For example, retailers might need to link the Gen AI to their own customer data. Marr (2024) details Walmart's adoption of a Gen AI solution that is connected to internal Walmart information, and thereby, it can help customers order, as well as assist staffers with information to answer queries. In the discussions with the retail vendor, we also learned that its retailer customer implemented a Gen AI solution that could link to both in-store data and company inventory data. Other situations favoring custom inputs include customer service and support use cases, those involving access to a company's internal knowledge, and those involving detailed content about a company's specific products or services.

Custom inputs can be provided in various ways (Davenport and Alavi (2023). The most common and least technically challenging is to employ retrieval-augmented generation (RAG), an approach that does not alter the training or variable weights of existing public or open-source generative models but instead revises the prompt-based instructions for specific models. If organizations seeking such customization have large volumes of content, they also need to apply vector databases or content similarity algorithms to feed the customized content selectively into the model. Customization using a company's own content requires that the content is well-curated and of high quality, currency, uniqueness, and so forth (Davenport & Tiwari, 2024).

However, in other cases, a general input might be preferable, as our discussions with the representative of a technology startup indicated. This firm possessed relatively little internal data. However, one of its goals was to post general content social media posts, for which general input may well be effective. ChatGPT, a general LLM using a general data set built from public sources, has proven especially successful in creating social media posts (Cook, 2023). Broadly, if the firm's goals include creating social media posts, initial drafts of sales scripts, and advertising drafts, a Gen AI

Table 3 Overview of extant Gen AI literature

Author (Year)	Insights for Marketing Practice
Benefits	
Brand, Israeli, and Ngwe (2023)	LLMs (ChatGPT 3.5) provide survey responses consistent with expectations from economic theory, highlighting potential uses for understanding consumer preferences
Capraro et al. (2024)	Gen AI–enabled sentiment analysis is accurate, relative to economic outcomes. Sentiment analysis is currently implemented by marketing practitioners to help respond to customers messages
Carlson et al. (2023)	Gen AI can be used to develop insightful and engaging syntheses of product reviews, with the potential to benefit retailers and consumers
Ghaffarzadegan et al. (2023)	Uses of Gen AI to build useful diffusion models that include realistic human reasoning and decision-making. Does not consider issues of bias in training sets or diffusion models. This benefit is important to social media marketers and other marketing practitioners that depend on viral content or word-of-mouth dynamics
Goli and Singh (2024)	LLMs can help marketing researchers understand preference heterogeneity. However, the preferences generated need to be carefully explored, because they can be misleading
Hirn et al. (2022)	Gen AI can facilitate pattern identification in complex, multidimensional data, effectively and efficiently, which can be useful for firms that are analyzing complex and multidimensional customer profiles that include, for example, buying patterns
Hubert et al. (2024)	Benefits of Gen AI in tasks that require divergent thinking, for which Gen AI outperforms humans and continues to improve, scoring in the top 1% of responses, which is valuable for marketers working on new product development or marketing research
Jackson et al. (2024)	Benefits include enhanced "efficiency, accuracy, resilience, and overall effectiveness," which are important considerations for supply chain practitioners
Jo et al. (2024)	Gen AI can preserve local identity through visualization in early design communications phases, manifested as financial and temporal efficiency, which has implications for new product development
Li et al. (2024)	The generation of synthetic data can be used for market research, to save costs and time
Yoshioka (2024)	Using synthetic data to develop a more accurate valuation for previously undervalued intangible assets showcases the benefits of Gen AI in financial analysis, a significant concern for marketing research practitioners too
Concerns/Risks	
Herbosch (2024)	Chatbots provide incorrect information, with legal implications, which are relevant to firms that use chatbots to help with sales or service processes
Levantino (2023)	Explores the role of civil society in regulating Gen AI and threats to fundamental rights and society, with implications for marketing and public policy
Markowitz (2024)	Gen AI's limitations for text analysis, including important implications for marketers who use sentiment analysis tools, for example
Monteith et al. (2024)	Issues of misinformation and ethics of using Gen AI in content generation, which pertain to marketers involved in content creation and deployment
Samuelson (2023)	Issues with intellectual property rights and the impacts of regulation, along with the possible risk of legal exposure for firms that deploy general LLMs
Implementation of Gen AI	
Andrieux et al. (2024)	Trade-offs in implementing Gen AI, including when to mitigate harm via human augmentation
Brüns and Meißner (2024)	Human augmentation in content creation is needed to mitigate negative attitudinal and behavioral reactions in followers
Kang, Kim, and Kim (2024)	Documents the creation of a custom LLM with human augmentation at the input phase
Langevin et al. (2023)	Proposes empirical design that can test both custom and general LLMs
Rossi et al. (2024)	Benefits of collaboration (human augmentation) with Gen AI, use of synthetic data, and corresponding ethical considerations, with use case and examples of general LLMs
Sleiman (2023)	Explicates the importance of selecting the right LLM and attention to regulatory concerns

solution based on a general that can access both more information and diverse information is preferable. Ultimately, the choice of input is within the firm's control, and should be made strategically based on the specific tasks it wants the Gen AI solution to address.

Beyond these influential considerations, several other points are noteworthy. Using a custom Gen AI model may help allay concerns about potential bias, because the firm has more control over the input information. To the extent bias is driven by the data in the Gen AI model, uses of a custom model might mitigate such bias, because it can be created

explicitly to limit bias. To the extent that ethical or legal concerns surround the data the model uses (e.g., appropriate copyright permission to use the information, such as rights to the input images or videos), adopting a custom model that has been created suitably and carefully, using only internal or free-to-use data, might reduce ethical concerns.

P1 The a) higher the need for a wide range of information and/or b) the lower the need for firm-specific information to generate the desired output, the more appropriate the use of Gen AI tools that use generalized input.

P2 The a) lower the risk from errors from inaccurate information, and/or b) lower the risk from privacy concerns, the more appropriate the use of Gen AI tools that use generalized input.

P3 The higher the a) need for proprietary or firm-specific information, b) risk of error from inaccurate information, and/or c) privacy concerns, the more appropriate the use of Gen AI tools that use customized input.

Level of human augmentation for Gen AI outputs

Some Gen AI solutions require limited or no human augmentation, such as Amazon's use of Gen AI to summarize customer reviews (Walk-Morris, 2023) or providing information about the location of a certain SKU in a retail store (Table 2). Because Gen AI tends to perform better in terms of speed than accuracy (Eastwood, 2023), a lack of human augmentation is most appropriate when the cost of any error is relatively low, allowing the firm to leverage the benefits of Gen AI, like speed and cost savings. But if the costs of a potential mistake are high (Eastwood, 2023), firms need to impose relatively more human augmentation. For example, the risks associated with an inartful or offensive social media post are fairly substantial. Therefore, an employee likely needs to review the generated content before it is posted on social media.

We propose that two factors should inform decisions about the amount of human augmentation: (1) the task type, which dictates the inherent risk involved, and (2) strategic firm considerations of the value proposition. Regarding the latter, a firm may opt for human augmentation even if risk is somewhat low. For example, both ChatGPT and Grammarly can respond to prompts related to ideation, but whereas ChatGPT requires no human augmentation (i.e., the output goes directly to the customer), Grammarly builds in human augmentation, suppressing responses to prompts that it deems "offensive," which then get reviewed by Grammarly, thus building "safety" (e.g., suppression of offensive prompts) into its value proposition, which is greatly valued by some customer segments (e.g., educational institutions).

Independent of the risk, greater human augmentation can provide additional benefits. Although Gen AI increases efficiency, the effectiveness of its output remains in question (Zhou & Lee, 2024). A recent test, comparing ads created by Gen AI with ads created by a human creative team, reflects this dichotomy (Erdem & Sidlova, 2023). The Gen AI ads prompted three times higher click-through rates, but the human-created ads generated 9.5 times as many leads (AIT News Desk, 2023). Baker (2024) adds to this discussion, arguing that effectiveness represents the next frontier for Gen AI. For firms that implement Gen AI solutions for marketing tasks, stronger human augmentation efforts might enhance effectiveness, especially if the Gen AI output alone does not appear very effective.

Some companies may decide to leave the level of human augmentation—review and editing in particular—up to human end-users. But such an approach may be problematic, considering evidence that employees who have the agency to decide whether to review and edit Gen AI–generated content do not always make wise decisions. For example, in an experiment involving writing with Gen AI, Noy and Zhang (2023) find that among participants who had access to Gen AI to help with their writing, 68% submitted the model's initial output without editing it. Yet these researchers also find no correlation between the extent of human editing and the quality-related grade the participants received from evaluators.

P4 A) The lower the risks associated with Gen AI output containing errors and/or b) the weaker the linkage between the firm's value proposition and mitigating output errors, the more appropriate the use of Gen AI tools with lower human augmentation.

P5 A) The higher the risks associated with Gen AI output containing errors and/or b) the stronger the linkage between the firm's value proposition and mitigating output errors, the more appropriate the use of Gen AI tools with higher human augmentation.

Proposed implementation framework

Combining our findings from discussions in the field and the review of the extant literature, we extrapolate several key points. First, Gen AI solutions can be classified according to two dimensions: the nature of the input (general vs. custom) and the level of human augmentation (low vs. high). Second, there are trade-offs inherent to making strategic choices across these dimensions. To capture these insights succinctly, we propose a Gen AI implementation framework for firms (Fig. 2). The first dimension, on the horizontal axis, reflects the level of customization of the input for Gen AI solutions, ranging from relatively low (i.e., general LLMs) to

relatively high customization (i.e., custom LLMs). The second (vertical) axis relates to the extent of human augmentation before delivering the Gen AI output to the user, ranging from relatively low (i.e., nearly autonomous) to relatively high human augmentation.

The axes delineate four distinct quadrants, which are illustrated in Fig. 2. Quadrant 1 (Q1, *fastest, less control, more risk*) with general input and low human augmentation (e.g., summarizing customer reviews); Quadrant 2 (Q2, *slower, more control, some risk*), with general input and high human augmentation (e.g., Gen AI creates social media posts that are reviewed by a human employee); Quadrant 3 (Q3, *faster, less control, some risk*) utilizing custom input and lower human augmentation (e.g., Gen AI solution providing information about SKU locations); and Quadrant 4 (Q4, *slowest, most control, least risk*), offering custom input and high human augmentation (e.g., Bloomberg GPT creating an initial draft of a Securities and Exchange Commission (SEC) filing that is reviewed prior to submission).

Importantly, although our discussions imply dichotomous anchors, we recognize that most Gen AI solutions are positioned along these continua (Davenport & Alavi, 2023). For LLM input types, the two extremes are represented by ChatGPT (general) and Bloomberg GPT (custom), but multiple hybrid LLMs appear between them, such as Morgan Stanley's Gen AI solution—a general LLM that gets trained by RAG-based prompt-tuning, to improve the accuracy and relevance of the information it uses. Similarly, the two human augmentation extremes are represented by using ChatGPT for editing and using ChatGPT to create social media posts. In the former case,

no human augmentation takes place; the material goes into ChatGPT and comes back edited. In contrast, there is much human augmentation in the latter case, such that a human employee carefully reviews the draft social media post prior to posting. Somewhere in between is Grammarly, which will flag an offensive ideation prompt, pending subsequent resolution by a human employee. Even if Grammarly responds to most ideation prompts with output provided directly to the customer, in some cases, the prompts may be suppressed and require human augmentation.

Trade-offs and selection heuristics for practitioners

The framework (Fig. 2) illustrates trade-offs in each quadrant.

Quadrant 1 With Q1 tools, the Gen AI relies on general inputs for training and requires little human augmentation. Therefore, such applications are fast and relatively inexpensive, but they are less likely to be perfectly appropriate or accurate. These solutions raise privacy and regulatory risks, associated with the use of general inputs. Therefore, Q1 tools are ideally suited for tasks with limited risk of damage or liability due to incorrect or inappropriate action and little need for firm-specific data. If a firm uses ChatGPT to summarize recent customer reviews for an internal employee audience, any inaccuracies are unlikely to lead to substantial brand damage, so low human augmentation seems appropriate. In addition, ChatGPT possesses capabilities to summarize reviews fairly well, so its effectiveness should be reasonably high and sufficient.
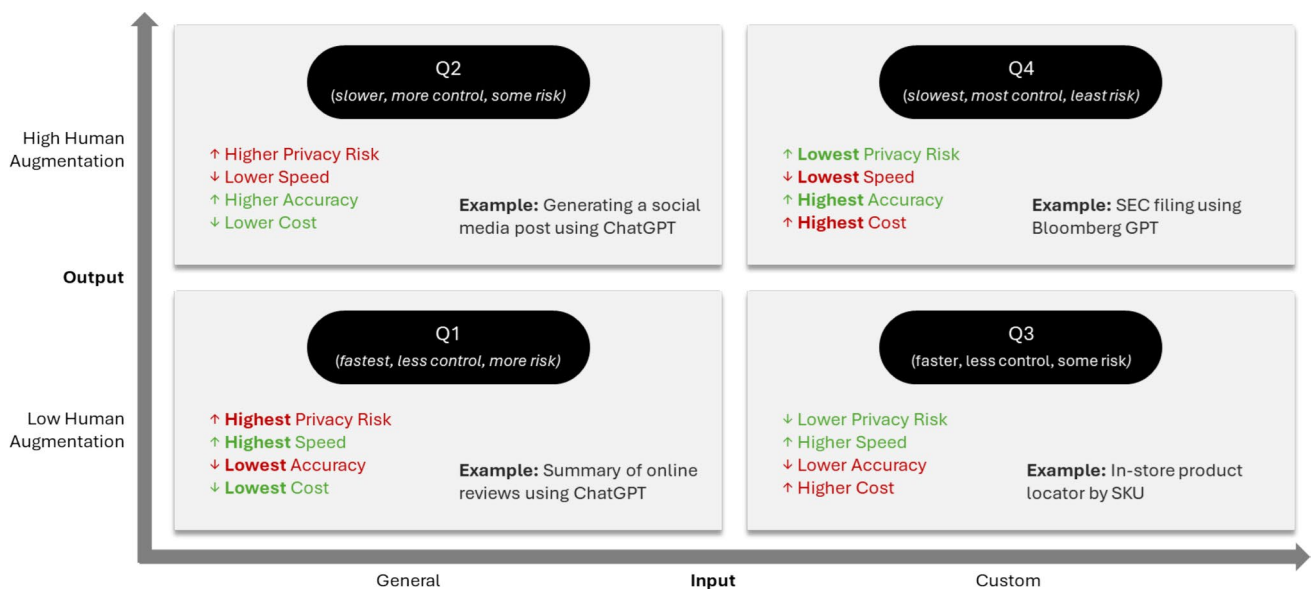

Fig. 2 Proposed generative AI selection framework

Quadrant 2 Like Q1, Q2 tools utilize generalized input, but unlike Q1, Q2 the output is coupled with more human augmentation prior to delivery. Output is delivered more slowly due to the inherent delay of adding human augmentation, but risk of inaccuracies and errors is mitigated. However, privacy concerns remain. Q2 tools are also more costly than Q1 tools due to the expense of human augmentation, but they remain less costly than solutions requiring a custom input (Q3 and Q4) and more likely than Q1 to be appropriate and accurate. Managers should select solutions in this quadrant when the risk related to an incorrect action is relatively higher, and the need for firm-specific information is lower. For example, considering the potential for substantial brand damage stemming from an inartful or incorrect social media post, high human augmentation is essential for generating social media content, but firm-specific data are not necessarily required to draft a sample social media post. Although human augmentation might increase the costs (time and money) or reduce response speed for Q2 tools, firms might choose to incur these costs, to ensure accuracy and appropriateness (i.e., greater effectiveness).

Quadrant 3 Q3 tools utilize customized input and low human augmentation. Output is delivered quickly, and privacy concerns are mitigated. However, risk of inaccuracy in the output remains. For Q3 tools, the specialized nature of the demand motivates the need for custom inputs. The solutions in this quadrant are best suited for tasks featuring a low risk related to incorrect actions but a strong need for firm-specific information. For example, a retail store might implement a Gen AI solution to provide SKU locations to its customer, which demands a custom, continuously updated data set depicting those locations. The risk of providing incorrect information is somewhat low though; customers might express a little frustration if they receive incorrect information, but it is unlikely to create significant brand damage. Therefore, no human augmentation is required, and by using a Q3 Gen AI solution, the retail store can gain speed and efficiency.

Quadrant 4 Finally, Q4 tools utilize customized input and high human augmentation. Output is delivered slowly, but privacy concerns and risks of inaccuracy in the output are mitigated. Q4 tools offer significant but expensive protection against risk. They offer reduced privacy and regulatory risks, due to their use of custom input, along with enhanced accuracy, due to their reliance on human augmentation. These solutions are best suited for tasks for which the risks related to incorrect action and inaccuracies are very substantial, and the need for firm-specific information is significant. For example, a firm might use Bloomberg GPT to generate its SEC filing documents. The specialized nature of the required information suggests the need for a custom LLM, and Bloomberg GPT was trained "from scratch" on a large volume of financially oriented content. Other benefits include the (relatively) accurate information and (relatively) reduced levels of bias or objectionable outputs. Noting the potential for substantial financial damage stemming from an incorrect SEC filing, high human augmentation is essential; such human augmentation can increase the effectiveness of the SEC filing too (e.g., in the Management Discussion and Analysis section). The temporal and monetary costs required might be high, but firms choose to incur them to avoid the significant risks associated with inaccurate, biased, or hallucinated output for this task.

Such trade-offs imply that firms must make suitable, careful design choices when they create or deploy Gen AI solutions. Human augmentation of Gen AI output is costly in both time and money but can improve the accuracy and effectiveness of the output. Depending on the intended goal for implementing Gen AI, it might be useful to incur the (sometimes substantial) cost of creating custom inputs (versus general inputs). In other cases, there are clear benefits of using general inputs, but doing so might increase the need for costly human augmentation to improve the accuracy and appropriateness of the final deliverable.

Limitations of Gen AI

As Gen AI continues to evolve and proliferate, it has significant potential for positive impact. But it also raises concerns that merit examination. For example, Gen AI solutions grapple with potential *infringement of intellectual property rights* (IPR). This concern is likely more relevant to Gen AI solutions using general LLMs, which draw from a wide body of content. When creating new output in response to user prompts, Gen AI potentially creates output that may infringe on IPR (Susarla, 2024; also see Table 2), which represents a serious concern, especially in creative contexts. As Susarla (2024) cautions, both individual and corporate users of Gen AI arguably can be held liable for such infringements. Referring specifically to DALL-E 3 and Midjourney, Marcus and Southen (2024) recognize their capacity to copy protected materials, as well as their failure to offer clear information about the sources from which they might have copied materials. If users adopt the output without question, they could inadvertently infringe on the original creator's IPR. Thus, the possibility of IPR infringement creates legal risks for both the Gen AI and the Gen AI user, above and beyond the business risk to the content creator. It is difficult to know just how serious these legal risks are; they are likely to remain the subject of legal action for many years.

Another concern applies to all types of Gen AI solutions, namely, the *creation of misinformation*. Gen AI can be exploited to create convincing "fake content" such as deepfake videos, forged documents, or realistic-looking images. This capability raises concerns about inappropriate content, identity theft, and fraud; malicious actors could use such content for deceptive purposes, especially during elections,

as demonstrated in recent years (Wirtshafter, 2024). At a broad level, this ethical concern should intensify considerations of how to decide which uses Gen AI should and should not support. Note that this issue rises over and above concerns linked to *hallucinations*, meaning Gen AI produce factually incorrect content.

When it comes to *privacy concerns*, a key concern is that any output created using Gen AI, or any materials input into the Gen AI as prompts, might be "appropriated" by the Gen AI, for use elsewhere. This specific point was raised in our discussions with senior managers, and it could be especially serious (and damaging) if the data include sensitive corporate or personally identifiable information. Many large companies have established agreements with LLM providers to prevent such content leakage, but executives remain concerned about this threat.

Turning to issues of *bias*, Gen AI algorithms might accentuate biases inherent in the data (Nicolletti & Bass, 2023). This concern is particularly relevant to Gen AI solutions using general LLMs, which typically include non-curated content from the internet. Such considerations imply a vicious cycle: As digital content increasingly gets generated by AI, the foundational biases spread, perpetuating and reinforcing harmful stereotypes (Nicolletti & Bass, 2023). The expanding reliance on and reach of Gen AI, in various marketing applications and daily life, grants this concern even greater significance.

Finally, there are concerns related to *opacity* (Yu & Guo, 2023). It is difficult or even impossible to explain the algorithms underlying Gen AI, which can be an issue in certain industries, particularly those that are substantially regulated. Furthermore, it may prove difficult to address other critical issues (e.g., privacy, IPR, bias) if the mechanisms that allow for such ethical transgressions are unclear, inexplicable, or inaccessible. In turn, firms could be vulnerable to liability, without a means to correct the underlying issues.

Research opportunities

Gen AI and its applications remain in their infancy, suggesting a plethora of opportunities for continued research. As we indicated previously, the marketing discipline should take the lead in research into Gen AI (JP Morgan, 2024), and we outline three distinct categories of research topics for such exploration, as summarized in Table 4, related to (1) Gen AI input, (2) Gen AI output and deployment, and (3) regulatory and societal issues.

Research topics related to Gen AI input

Researchers should define precise parameters for determining the need for custom inputs, such as Bloomberg GPT's Gen AI solution (Davenport & Alavi, 2023), versus easier-to-create RAG models using prompt-tuning. Popular wisdom holds that custom inputs offer performance benefits; the Bloomberg GPT model outperforms existing open models of a similar size on financial tasks by large margins, while still performing on par or better on general natural language processing benchmarks (Bloomberg, 2023). Yet Li et al. (2023) suggest that ChatGPT 4.0 (a general LLM) can hold its own against, if not achieve better performance than, BloombergGPT. Therefore, we do not yet understand the boundary conditions that determine whether investing in a custom LLM will reap the returns needed to justify the expense or what type of customization is most effective in specific circumstances. Such boundary conditions are complex and ever-changing, so they also need to be tested formally, and then retested, to establish the actual benefits of using a custom LLM. Considering the potential for multiple objective goals (e.g., accuracy, speed, cost), the boundary conditions that affect the choice between a custom versus general input (whether for LLMs or multimodal and LVMs) may have differential impacts.

Researchers also might explore lower-cost alternatives for creating custom inputs. Davenport and Alavi (2023) suggest fine-tuning the training of an existing LLM with specific domain content; Google implemented this approach when building a medicine-focused LLM. Alternatively, as we noted previously, prompt-tuning modifies a general LLM using a set of suitable contents, as demonstrated by Morgan Stanley (Davenport & Alavi, 2023). The cost of creating and updating a custom LLM is non-trivial, and the effort itself is difficult (Shah, 2023), so finding lower-cost, viable alternatives is pertinent, especially considering the benefits of using custom inputs.

Some Gen AIs establish value propositions associated with assuaging privacy concerns. For example, Grammarly's Gen AI solution promises that it will not absorb any content created by its users or data made available in users' prompts into its LLM. Several providers make similar promises about the general LLMs they offer; other Gen AI solutions do not make any such promises. Some firms employ open-source models (e.g., Llama) in private clouds to address privacy concerns. Researchers should examine how Gen AI users balance increased privacy and IPR protection versus, for example, reduced costs to implement and deploy a Gen AI solution. We need scholarly attempts to probe the boundary conditions of when the benefits of privacy and IRP protections result in adequate returns on the investments needed to institute such protections.

Research topics related to Gen AI output

A key issue relates to bias: Gen AI can amplify the biases present in an LLM. Scholars should explore when and how to measure, manage, and mitigate bias in outputs. Beyond managing the LLM, two possible approaches entail altering

Table 4 Research avenues

Topic	Important Questions for Research
#1: Gen AI input: Understanding the inputs (e.g., text, images, video) into the LLM and alternative ways to build LLMs (or LVMs)	• Given some desired Gen AI output, which LLM is optimal: custom LLM, general LLM, or an integrated version? What are some factors that inform such choices? How do these questions extend to multimodal models or LVMs? • What are some methods for improving a general LLM, such as prompt-tuning (improving inputs)? Can a custom LLM be useful outside the specific use case for which it was built? • What are the costs and return on investments for ensuring better privacy and reduced IPR infringement in newly developed Gen AI solutions? What factors affect the decision to offer increased privacy and/or reduced IPR infringement?
#2: Gen AI output and deployment: Understanding the outputs of the proposed Gen AI solution and the level of human augmentation needed	• Which biases are associated with different Gen AI solutions (according to their inputs), and how can they be managed or mitigated? • To mitigate biases, is it optimal to manage the LLM input, manage the algorithm, or manage the output through human augmentation? • Considering ethical and public policy quandaries, which applications should avoid the use of Gen AI? How can firms and individuals be dissuaded from pursuing such applications (e.g., election-related deep fakes) or creating unethical Gen AI outputs? • What options are available to increase transparency and returns on investments in Gen AI solutions? How should firms think of balancing risk versus returns in their Gen AI investments? • What insights might be derived from classifying Gen AI, similar to the classification of analytical AI, into mechanical, thinking, and feeling types? Is another classification more appropriate for Gen AI?
#3: Regulatory and societal issues	• Can newly proposed and implemented rules and regulations enhance (or detract from) Gen AI innovation, solutions, and returns? • How should we measure the trade-offs evoked by rules and regulations involving privacy, IPR, and other societal concerns, across various Gen AI inputs, outputs, and overall social impacts? • Will certain Gen AI solutions advance or hinder human social skills? How will such influences change society?

the algorithm or applying human augmentation, or some combination of both. Specifically, firms could manage bias by including costly human augmentation processes, such as careful reviews prior to the delivery of any output, when it seems necessary. But humans also suffer from bias. Scholars thus might attempt to quantify the interaction between human mediator bias and LLM bias, while also exploring other, perhaps less costly, more efficient, and/or more effective ways to mitigate biased output. Another route to addressing bias involves improving the underlying Gen AI algorithm. Like the humans who design them, algorithms are not neutral. According to recent, international research involving 14 LLMs, "OpenAI's ChatGPT and GPT-4 were the most left-wing libertarian, while Meta's Llama was the most right-wing authoritarian" (Heikkila, 2023). Such bias creates risks, especially as Gen AI becomes increasingly involved in various marketing (and other) tasks. Nor can all the bias be attributed to raw data, because it also reflects the weights of and adjustments to the underlying model. Research can explore bias at each level and examine alternative options for measuring, managing, and mitigating bias. This discussion presumes that Gen AI solution providers are seeking to avoid bias; it may be that some providers have less concern about bias or even embrace certain types of bias.

Relatedly, scholars should probe the boundaries of ethical uses to determine if there are some tasks for which Gen AI should not be used. Such questions are particularly challenging for practitioners because these refer to both firm-level priorities and policy-level preferences. Scholars might provide empirical evidence related to how context- and task-specific boundary conditions vary (e.g., Wirtschafter, 2024), and the resulting insights could help guide developments of, for example, counter-AI tools that can detect Gen AI attempts in certain domains (e.g., detecting deep fake images). If scholars explore these boundary conditions, they also could establish policy recommendations for how to craft effective legislation, such as requiring watermarks on Gen AI images, or other regulations specific to Gen AI providers. Some technology moguls (e.g., Elon Musk) and leading AI researchers (e.g., Yoshua Bengio, Stuart Russell) already have called for a pause in Gen AI development (Narayan et al., 2023).

A related area for scholarly exploration pertains to risk (e.g., Haidar, 2023; Vartak, 2023). One of the senior executives we interviewed, employed by a *Fortune* 500 company, indicated both excitement and significant trepidation about the deployment of various Gen AI solutions. They noted concern about the opportunity costs of not deploying Gen AI solutions, along with an equal measure of concern about risk exposure in deploying these tools (e.g., malicious use). Risk researchers could help assuage these concerns by outlining ways for practitioners to measure, mitigate, and report the risks they assume when deploying a Gen AI solution. Such efforts will represent a complex and difficult endeavor, but it

remains critically necessary to find a way forward for practitioners and address broader issues, including but not limited to marketplace freedom and personal space.

In relation to opacity (Yu & Guo, 2023), an interesting discussion surrounds the benefits of developing less opaque Gen AI algorithms. This line of research might start with the themes proposed by Rai (2020), who argues that the benefits of explainable AI stem from either the domain (i.e., government requires the use of explainable algorithms) or customer desire (i.e., customers are more willing to pay more for or adopt explainable Gen AI solutions). Researchers might use these themes to understand when the use of a relatively opaque Gen AI may lead to complications. Other researchers might examine ways to create less opaque Gen AI versions.

Most of these concerns involve risks related to Gen AI, but we also call on scholars to investigate ways to turbocharge the *returns*. For example, might Gen AI create text, images, video, and audio output that not only systematically rivals human-created content but also is highly relevant to marketing applications? Although JP Morgan (2024) acknowledges the benefits of current research into LLMs and algorithms, it also predicts that Gen AI will move towards "edge AI"—that is, decentralized computation loads that expand the benefits to end-users. Carlson et al. (2023) already have started to explore how deep learning and neural network–based Gen AI can develop online reviews that could be useful to consumers and managers alike. Accordingly, we call for research that recommends future moves, given the potential returns from Gen AI.

Research should also examine the conditions that allow for the productive deployment of Gen AI models (e.g., Satornino et al., 2024), to support the generation of economic returns, rather than just "proof of concept" experiments. Survey research (Davenport and Tiwari, 2023) suggests that a low percentage of companies (e.g., 6%) have deployments actually in place. Most companies are experimenting at individual or departmental levels, but it is production deployments that are likely to induce changes in employee skills, business processes, strategies, and business models. Researchers could identify some important, non-technological human augmentations needed to deploy Gen AI projects that support the pursuit of productivity benefits and economic value (Brynjolfsson et al., 2021).

Finally, prior work has classified analytical AI into mechanical AI, thinking AI and feeling AI (Huang and Rust 2021a, b), which could offer a useful framework for thinking about different types of AI and how to deploy them. As we noted, Gen AI output reflects all three domains and can be used to conduct mechanical, thinking, and feeling tasks (Spair, 2024; Walk-Morris, 2023). The question that remains though is whether this specific classification is useful for Gen AI. With regard to analytical AI, Huang and Rust (2021) argue that mechanical AI is probably the easiest to execute, whereas feeling AI is the hardest and thus is likely be the last domain implemented in practice. Such predictions also might extend to Gen AI, but it is critical to consider if and how this classification should be adapted to reflect the unique aspects of Gen AI. Analytical AI has been deployed in the field for longer, and our understanding of its advances and the related technologies have improved over time; we have less clear insights into the relevant mechanisms for ensuring the advancement of Gen AI.

Research addressing regulatory, societal, and social issues associated with Gen AI

Continued research might address three other notable issues. First, we need a better understanding of the impact of *regulation*. A variety of laws related to AI have passed, and some even make specific references to Gen AI. The in-process EU AI Act (AIA) not only attempts to define Gen AI but also contains specific provisions for it (Barani & Van Dyck, 2023), such as efforts to curtail IPR infringement and restrict manipulative, deepfake content. Lee, Lucchini, and Lee (2024) predict that both the General Data Protection Regulation (GDPR), in effect since 2018, and the AIA, which entered into force in August 2024, will transform the Gen AI market. Accordingly, we call for research into the likely impacts of current and proposed regulations on Gen AI advancement, proliferation, and innovation.

Second, investigations of the *longer-term societal impact* of Gen AI will be helpful. Considering its exponential growth, Gen AI is likely to continue to advance in the coming years. In so doing, it could threaten various job functions, including white-collar tasks (e.g., marketing researchers, analysts, content creators). Its ability to generate content also might mean that Gen AI applications could serve effectively as virtual companions. In this sense, the cost-related benefits of highly advanced Gen AI seem obvious, but its implications for *capability* and *social issues* are less so. If Gen AI performs various tasks, then human capabilities linked to such tasks atrophy, with substantial repercussions. Scholars in human behavior and marketplace dynamics domains might explore the implications of Gen AI–driven losses and acquisitions of capabilities, to help prepare practitioners, policy makers, and marketplace participants for positive progress.

Third, turning to related *social* issues, if Gen AI–powered applications can serve as effective substitutes for human interaction or virtual companions, the seeming deterioration of social skills and community cohesion in today's societies may continue to worsen (Grewal et al., 2024). Scholars should explore the potential for negative repercussions of increasing social distance within organizations, communities, and regions, as implied by the increased use of Gen AI to address social needs. We also need ideas for how to

assess and mitigate such deterioration of social structures. More powerful, believable, and capable proxies, driven by Gen AI, could have notable implications for social atrophy, and we need research into potential human augmentations to prevent the complete breakdown of communities.

Conclusion

Generative AI has radically transformed the business landscape, with particularly strong impacts on marketing. As such, marketing scholars must take the lead to make sense of this rapidly evolving space and provide guidance to managers eager to capitalize on the spectacular benefits of Gen AI, particularly in elevating the efficiency and effectiveness of their marketing function. Such guidance must encompass not only ideas for how to deploy Gen AI in ways that suitably enhance value but also suggestions for how to navigate the risks and complexities associated with Gen AI solutions. By building on prior work and interviews with senior managers and Gen AI users, we determine that, when choosing to deploy Gen AI, key concerns relate to Gen AI inputs (general versus custom inputs) and Gen AI outputs (extent of human augmentation, prior to deployment to the end user). Contingent on the Gen AI task, its value proposition, the risks associated with any Gen AI error or miscommunication, and the costs, firms must make careful, suitable choices and trade-offs of their Gen AI input and output. To this end, we propose a framework (Fig. 2) to provides relevant, much needed guidance.

We also outline various limitations and concerns associated with Gen AI. Like analytical AI (Davenport et al., 2020), Gen AI raises concerns related to data privacy, embedded algorithmic bias, ethics (including whether certain Gen AI applications should even be considered), and opacity ("black box" nature of the algorithm). Other concerns are unique to Gen AI though. First, it is vulnerable to "hallucinations," in the sense it provides erroneous output, on a scale very different from that possible with analytical AI. Second, Gen AI is especially amenable to the creation of disinformation, which has substantial public policy implications. Third, Gen AI output, especially creative forms (text, images), can infringe on IPR, with consequent risks for Gen AI creators and users.

The Gen AI research agenda that we propose covers three broad areas (1) Gen AI input, (2) Gen AI output, and (3) concerns associated with Gen AI. The topics contained within this research agenda warrant consideration by academic researchers, firms that create Gen AI applications, Gen AI users, and policy experts. Gen AI already has exerted notable impacts on marketing; it will continue to have substantially more impact in the days and years ahead, and there is much still to learn. We hope that this agenda motivates, and structures continued research into Gen AI.

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