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REPLACE, ADD, AUGMENT
A POSSIBLE CLASSIFICATION FRAMEWORK FOR AI MARKETING

In the current wave of enthusiasm for AI marketing, one of the most recurring considerations is that its potential can only be fully realized when AI is used in collaboration with human intelligence, not as a replacement for it. However, to avoid oversimplification in an extremely heterogeneous landscape, it is important to take a more nuanced perspective, invoking several relevant dimensions to classify marketing processes according to the role that AI can play. In doing so, three main strategic options for management emerge: processes for which AI should be considered to completely replace human intelligence; processes for which iterative human-machine collaboration can generate enhanced synergistic value; and processes that can be implemented from scratch to delegate the creation of new customer value to AI. After elaborating on these areas, the "Replace, Add, Augment" model is then introduced to better focus on the infinite spectrum of AI applications in marketing.

MARKETING//INNOVATION//ARTIFICIAL INTELLIGENCE//GENAI//AUGMENTED MARKETING

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INTRODUCTION

The development of artificial intelligence, and in particular generative AI (GenAI), has turbocharged the transformation of marketing processes. But what exactly is GenAI? Let's start by defining AI. The most common view in the literature describes it as the set of technologies, algorithms, and models (that is, machines broadly defined) designed to emulate human functions such as learning, reason, and goal attainment (Davenport et al., 2020; De Bruyn et al., 2020; Huang and Rust, 2021). Within this generic boundary, GenAI represents the subset of technologies and models that attempt to mimic human cognitive functions by creating different forms of content, such as text and images. Methodologically, the operation of these systems requires highly sophisticated statistical techniques and a training phase involving algorithms with impressive amounts of pre-existing content. In other words, generative AI enables combinatorial creativity, that is, it produces new outputs by combining existing elements. (Indeed, a related, much debated issue is how to compensate the authors of the original content used to train these models.)

The potential and implications of AI are so huge that there is talk of a paradigm shift, an expression introduced in 1962 by the philosopher Thomas Kuhn to describe human progress as alternating between periods of relative stability and moments of revolutionary breakthroughs "in fundamental concepts and practices." The economist Dosi (1982) later adapted this idea to the world of technology and production, introducing the concept of a technological paradigm to describe a clean break with the past, capable of opening up new trajectories of development and transformation. Strictly following the contours of these concepts, AI does not represent a true paradigm shift, as it still fits perfectly within the broader digital paradigm, the dominant frame of reference of our time.

However, artificial intelligence can also be seen as a "new trajectory of development and transformation" enabled by the current technological paradigm – a "technological trajectory" within a broader "digital paradigm." GenAI, a further evolutionary leap, can be described as a new trajectory that branches off from the broader path of AI progress. As we'll see, this trajectory is particularly relevant to the ability of new models to learn and respond as a function of their autonomous understanding of context. It is no coincidence that GenAI is often discussed in terms of its possible approximation to AGI (Artificial General Intelligence), i.e., a hypothetical system capable of perfectly mimicking the power and flexibility of human intelligence. Consistent with this, the technology literature on such solutions sometimes uses the term General Purpose Technology (GPT), that is, technology capable of significantly impacting different sectors of the economy and society, with pervasive and transformative effects on the way people work, communicate, and live (Bresnahan and Trajtenberg, 1995; Brynjolfsson et al., 2017).

In marketing, AI began to take hold in the early 2000s by optimizing direct marketing campaigns and communications investments deployed via search engines and other digital channels. Over the next decade, its use gradually expanded with new tools for brand monitoring, sentiment analysis, and social media management. Year after year, data and algorithms became an increasingly salient component of marketing activities, supporting descriptive, diagnostic, predictive, and prescriptive analytics (Arbore, 2023). This brings us to the early 2020s, with the advent of generative AI. As we all know, the so-called "jump over the abyss" and subsequent mass adoption occurred with the launch of ChatGPT-3, the killer application released for free by OpenAI in late 2022, which amassed its first 100 million users in just two months (source: OpenAI).

Macro applications

First of all, for the marketing function, GenAI is promising in certain macro-settings:

- For market sensing (or upstream marketing), i.e., to support all activities undertaken to observe, listen, and understand customers better, in particular by analyzing the infinite amount of user-generated content (UGC) and digital footprints left by users online.
- For creative processes that cut across marketing at various levels, from developing new solutions to communicating value.
- For customer interaction processes that are equally cross-functional and present throughout the entire customer journey, from initial information seeking to customer support and relationship management.

In all of these cases, the characteristics of AI – and especially GenAI – raise high expectations for the potential impact, both in terms of process efficiency and, in some cases, effectiveness. Not surprisingly, experimentation is proliferating in activities such as social media listening (market sensing), brainstorming (creative processes), sending personalized communications (interaction processes), customer support (interaction), SEM and SEO optimization (creativity and interaction), and so on.

Another application area could be knowledge sharing, particularly internally, about the market and customers, helping to overcome traditional organizational silos. Unstructured data, such as social media posts or call center conversations, could also be used for this purpose.[1] From this perspective, an ideal generative AI tool, trained and fueled by any type of internal and external information about prospects, customers, and competitors, could become a veritable corporate oracle, accessible to anyone in the organization for specific marketing or, more generally, customer-centricity-related purposes. This hypothetical tool would finally overcome the technical barriers of internal information systems, which often cannot talk to each other, as well as the practical barrier of finding the right information from the right source at the right time. Of course, there are risks that would need to be carefully addressed in these cases (in addition to the current limitations of GenAI). One is the potential leakage of sensitive information, especially for generative AI tools hosted on external servers. In addition, if these tools were to rely on third-party models, corporate data could be used to train them, paradoxically providing an advantage to other organizations, including competitors.

Beyond theoretical assumptions, execution will be one of the key variables, with all its technological and, more importantly, organizational pitfalls. At this stage, with all the hype, it's impossible to predict with any certainty the real future impact of these technologies, not only from a business point of view, but also at a societal and regulatory level.[2] The management literature for the most part reports extreme cases on the ground, both positive and negative, on an anecdotal basis. But the outcome of many other experiments underway in large and small companies, both in Italy and abroad, remains uncertain. These developments will have to be a research priority in the immediate future. Zooming out from the micro to the macroeconomic level, forecasts vary: Goldman Sachs expects productivity to increase by 1.5% over ten years, while more conservative estimates (see MIT) limited that number to 0.5% over the same period (Warner and Kessler, 2024).

TOWARD AN INTUITIVE MANAGEMENT FRAMEWORK

As the current literature still seems either too fragmented or focused on specific applications, an interpretive key is needed to refocus the role of AI and GenAI in marketing. This paper aims to go beyond the macro-settings outlined so far and provide more circumscribed, albeit still relatively broad, guidance for management and companies. From a methodological point of view, the analysis will build on what is already available and established in the literature that studies and classifies the organizational processes of firms. Within this framework, we will then identify and cross-reference the most useful and relevant constructs for the purposes of our research.

Generally speaking, algorithms and machines are particularly effective in automating structured tasks, but GenAI can now play an extremely interesting role in unstructured tasks as well. This fundamental task classification, originally introduced by Thompson (1967) and elaborated below, should be interpreted as a continuum whose endpoints are perfectly structured tasks and wholly unstructured tasks.

1 "Structured" data is collected, organized, and stored according to a predefined format. In contrast, "unstructured" data lacks a specific format and typically includes text-rich content (such as emails or social media posts), images, video, and audio files. Unstructured data cannot be easily organized into rows and columns, making it more complex to analyze using traditional methods. In these cases, GenAI systems must first format and standardize the unstructured data, transforming it into structured data (known as preprocessing activities); these data can then be further processed by AI to extract relevant insights (Paschen et al., 2019).

2 On the risk front, the following public repository, initiated by MIT, is a notable resource: "The AI Risk Repository" (airisk.mit.edu).

Structured tasks

Structured tasks, or easy tasks (Alavi and Westerman, 2023; Acemoglu, 2024), are characterized by clearly defined inputs and outputs, accompanied by equally clear and predefined procedures for turning inputs into outputs. Selecting the best keywords to optimize the click-through rate of an SEM campaign is an example of a relatively structured task. In general, algorithms and machines outperform (or at worst, equal) humans in terms of efficiency and effectiveness in these types of processes, thanks to several distinguishing characteristics:

- Extremely superior speed and processing power.
- Impressive computing power.
- Unmatched memory capacity.
- Endless patience and attention (not-to-be-underestimated soft factors).
- Negligible marginal costs (except for fixed or semi-fixed costs).

For structured tasks, AI algorithms are usually based on transparent, well-defined rules (if, then), such as decision trees or statistical models with a limited number of parameters. For this reason, they are sometimes referred to as white-box algorithms (or *white box AI*, as in Candelon, 2023), since the process leading to each output can be fully understood – and thus fully controlled – by humans.

Unstructured tasks

The very nature of more structured tasks makes AI an ideal substitute for human intelligence (even before GenAI), freeing up cognitive resources that can be devoted to more complex tasks. These include, by definition, unstructured tasks that involve greater ambiguity and variability in both the outcomes and the procedures required to achieve them. (A very similar concept recently introduced in the literature is the hard task.[3]) An example would be developing a content marketing strategy. Until recently, computers and algorithms were woefully inadequate in dealing with such challenges. But with the latest innovations in modeling, particularly the development of deep neural networks and large language models (LLMs), things have changed rapidly.

This new breakthrough was possible because generative AI and other more advanced AI models not only perform specific tasks; they also continue to learn beyond their initial programming (Davenport et al., 2020). What's more, these systems are able to interpret the broader context, or at least they try. In fact, this impressive capability is also their main limitation, since this is where we lose full control over their output. Here's what we mean by that. The contextual awareness of these models is based entirely on a set of statistical inferences largely unknown to both the user and the model developer, and not on a set of programming rules defined ex ante, nor on true semantic reasoning like we humans use. Fittingly, these systems are also known as *black-box AI* (and an increasingly relevant area of study is *Explanable AI* (XAI), which seeks to make their results more transparent and understandable to humans.) For the same reason, when these systems fail, they fail spectacularly, with completely incorrect or meaningless answers (which are called hallucinations).[4]

Based on our discussion above, with respect to unstructured marketing tasks, generative AI can indeed play a supporting role in augmenting human capabilities (which is also known as co-piloting), improving both the efficiency and effectiveness of managing these processes. However, it cannot replace human intelligence. In B2B marketing, for example, the use of AI tools to support sales teams

3 "Hard tasks typically do not have a simple mapping between action and desired outcome. In hard problems, what leads to the desired outcome in a given problem is typically not known and strongly depends on contextual factors, or the number of relevant contexts may be vast, or new problem-solving may be required. Additionally, there is typically not enough information for the AI system to learn or it is unclear exactly what needs to be learned." (Acemoglu, 2024, p. 16).

4 As philosopher Luciano Floridi recalls, referring to LLMs, these systems "do not think, reason or understand; (...) they can do statistically-that is, working on the formal structure, and not on the meaning of the texts-what we do semantically, even if in ways (ours) that neuroscience has only begun to explore." (Floridi, 2023, p. 1-2).

is becoming more and more common, particularly for scoring accounts based on likelihood of purchase or abandonment. With GenAI, these algorithms can now use unstructured data about customers, such as the tone and content of a conversation, social media posts, or email messages, to make more specific and timely suggestions to salespeople, who are still irreplaceable. Conversely, when GenAI or other black-box algorithms are used to replace humans in managing unstructured tasks to reduce costs, as in the case of customer support, companies risk compromising the effectiveness and control of these activities. Similarly, when the task is highly structured, choosing a complex black-box model over a simpler white-box algorithm may offer small gains in effectiveness, but at the risk of substantial losses in control and transparency (see also Candelon et al., 2023). Managing these tradeoffs will be a critical challenge in the coming years. To support this goal, we will attempt to draw conclusions in the next few sections by presenting a summary conceptual framework.

Other classifications

For the sake of completeness, we should note that other authors suggest classifying AI technologies according to the difficulty of the tasks they can solve but applying slightly different labels than the ones we've used so far. (At this stage, however, the proliferation of new labels is not always useful; whenever possible, we suggest reusing already established constructs such as those listed above.) In particular, Huang and Rust (2018, 2021) distinguish three cases: (1) *mechanical (*or *narrow) AI*, purposed to automate repetitive and routine tasks, utilizing systems which lack the flexibility of human intelligence; (2) *thinking AI*, designed to process data to arrive at new conclusions or decisions; and (3) *feeling AI* (sometimes referred to as *emotional AI*), designed to best interact with humans and analyze feelings and emotions, as the name would suggest. Huang and Rust (2022) also explored the possible cooperative relationships between AI and human intelligence in marketing, citing AI's strengths in mechanical and analytical intelligence, complementing the contextual, intuitive, and emotional intelligence that are the hallmarks of human beings.

The points of contact with the classification proposed here are obvious, and some of these dimensions will reappear in the presentation of the summary scheme. In the following sections, we will outline the managerial implications, cross-referencing the most useful dimensions. Our aim is to develop a simple model capable of classifying the marketing macro-opportunities offered by the new technological trajectories. To achieve this goal, we will first present some real-world applications that illustrate in concrete terms the possibilities that companies are exploring in these early stages. This will also be an opportunity to discuss the risks associated with such initiatives.

GENAI IN MARKETING AND POSSIBLE RISKS

Contextual awareness, combinatorial creativity, and the ability to use even unstructured data are characteristics that raise high expectations for leveraging generative AI in marketing. In this exploratory phase, companies are testing its applications for structured and unstructured tasks along the continuum introduced earlier. As early as 2023, for example, Meta launched a generative AI service for advertisers to create and optimize marketing campaigns on social channels by crafting and then comparing multiple versions of text and graphics. Incidentally, this is consistent with what we call an abductive marketing approach, which is particularly suited to environmental contexts that are more and more unpredictable, but where real-time feedback from the market is possible.

Moving from the structured processes of digital campaigns to much less structured ones, companies are again exploring the use of generative AI to replace humans, sometimes for existing activities such as customer service, sometimes to provide customers with additional services not previously offered. In the latter case, for example, Expedia announced the integration of ChatGPT into its app, allowing users to plan trips and vacations thanks to personalized suggestions on destinations, attractions, and activities. Zalando has debuted a similar tool to help customers choose the perfect items for them from the selection available on the platform. Specifically, prospects will be able to describe to the chatbot the type of product they're looking for, using their natural language extensively; then they'll get invaluable help to scout out the most relevant offers in the vast catalog.

For the same purposes, more and more users are turning to new generations of artificial intelligence-based search engines, such as Google Gemini, Microsoft Copilot, or Perplexity for specific suggestions on what products to buy. This is raising new concerns about the possibility that some players can easily manipulate search results in their favor. Kumar and Lakkaraju (2024), for example, have already shown how adding a carefully crafted message (Strategic Text Sequence, STS) or specific codes on a product's information page can significantly enhance the likelihood that it will be mentioned among the products recommended by the chatbot.

As these purchase searches become more commonplace, companies now need to be aware of the critical nature of what we might call their AI reputation, i.e., how leading AI models perceive brands and products given their opaque statistical inferences. Will this be the new *zero moment of truth* in the customer decision journey? It should come as no surprise, considering the circumstances, that we are seeing the emergence of new companies like Profound that specialize in AI optimization (AIO): using millions of different prompts, they test and analyze the responses of AI models in relation to specific brands and products. Contextually, in the case of the more transparent engines, they also track all the websites cited as the sources of the responses. Companies can use these outputs to try to improve their rankings in chatbot responses, applying techniques and tricks that are very reminiscent of search engine optimization (SEO). In fact, as with SEO, leading providers of AI-based engines are constantly rolling out new measures to strengthen their models and make them less vulnerable to external manipulation (Roose, 2024).

In other examples of experimentation, companies such as Adidas, Nike, and H&M have begun to use generative AI to assist in the brainstorming process for new collections or above-the-line advertising campaigns, sometimes even involving their own communities. By the same token, AI has been used to develop new products or lines for the past decade. For example, the fast fashion company Choosy, mainly inspired by trending posts on Instagram, launched several designs a week that customers could order even before they went into production (Pallant and Sands, 2018). All these cases give us the cue to continue the discussion by emphasizing how AI-related marketing initiatives can also expose companies and their brands to various risks, particularly if the focus shifts from cost and efficiency to effectiveness and control.

AI marketing risks and opportunities

The use of chatbots for some customer interaction processes may excessively reduce our control, particularly with regard to recovery activities for service or support. The risk here is fatally exacerbating customer frustration. Some preliminary studies report that customers trust AI less because it's incapable of emotions (Gray, 2017; Davenport et al., 2020). Research confirms this for interactions or decisions that customers say require intuition and empathy (Castelo et al., 2019). Yet even given the preference for human interactions, AI can still provide back-end support for customer service. For example, AI can automatically intervene to assign each customer to the agent best suited to meet their needs (Campbell et al., 2020). In addition, the system can assist agents by synthesizing the most relevant information about the customer for them, another example of human-machine collaboration rather than risky substitution.

More broadly, both HR and customers may exhibit what's known as algorithm aversion, or an inherent reluctance to rely on automated decision-making systems and suggestions.[5] In this regard, a

2024 Salesforce survey of 11,000 people found that only half were willing to use AI to improve their customer experience. Other studies, although less recent, have shown that women in particular are less likely to adopt AI-based solutions. Understandably, the more transparent white-box algorithms tend to be more accepted than black-box models, which are inherently less clear.

Some studies in this area have also investigated the so-called *word-of-machine effect*, which occurs when algorithms churn out automated purchase recommendations for potential customers (Longoni and Cian, 2022; Longoni et al., 2019). This effect can be either positive or negative, depending on the context. Specifically, consumers tend to appreciate AI-based recommendations for utilitarian purchases with clear evaluation criteria, but they often show strong resistance when it comes to more hedonistic products. In the latter case, recommendations from other consumers lead to much higher conversion rates, especially among people with a strong sense of personal uniqueness. Finally, whereas previous studies found respondents to be more empathetic and less averse to robots (Kwak et al., 2013), more recent analyses have shown that customers' discomfort with AI intensifies when these applications are embedded in robots (Mende et al., 2019). However, this appears to be mediated by individual, demographic, and psychological factors (Mahmud et al., 2022).

As an extension of the idea of *algorithm aversion*, it is interesting to note that the Coca-Cola campaign developed for the 2024-25 holidays was created using generative AI, an element explicitly emphasized in the relevant messages, while maintaining the brand's nostalgic style and traditional tone. Public reaction, amplified by social media and the press, was far from positive. Some comments reported by the New York Times spoke of "disturbing perversions" that would no doubt ruin the spirit of Christmas (Vadukul, 2024). A decidedly negative reaction, and a signal seemingly consistent with the above, but in a broader sense: this reflects an aversion to possible algorithmic encroachment on the personal experience of the public. Another sore point that emerges in studies on chatbots and AI in general is the growing concern of customers about privacy, a constant even in the most recent studies. (See, among others, De Cremer et al., 2017, and Mani and Chouk, 2017. Further research on this topic is ongoing.)

Using artificial intelligence as a source of inspiration for business ideas, new product development, or the creation of new collections could expose companies to the risk of over-anchoring data that belongs in the past. This could lead them to follow market trends rather than anticipate or inspire them, as industry leaders should. However, this risk seems to be much more contained with the latest generative AI systems, which aim to enhance creativity rather than replace it. In fact, these models have also proven effective in stimulating disruptive ideas from management, particularly in companies that already had talented people on staff (Gregersen and Bianzino, 2023; Boussioux et al., 2024).

In this sense, it seems that generative AI can indeed play a decisive role in supporting creative problem-solving beyond product innovation. When combined with lateral thinking, it has been shown to promote both incremental ideas and innovative solutions. For example, Gregersen and Bianzino (2023) report the case of Colgate-Palmolive, which experimented with GenAI to analyze how coal became an in-demand ingredient in the United States, with the goal of identifying the next successful ingredient. The algorithm's initial answers prompted the team to ask additional, less obvious questions, stimulating creative thinking about future trends in different product categories, with results that are looking encouraging. Boussioux and colleagues (2024) have also explored these issues, comparing the innovative potential of ChatGPT with that of crowdsourcing to create new business ideas in the context of the circular economy. The researchers found that people tend to come up with more creative and disruptive ideas, but this process is costlier and more time-consuming, while AI is able

5 For a more extensive review on the topic of algorithm aversion, see: Burton et al., 2020; Mahmud et al., 2022; and Haupt et al., 2024.

to propose more practical solutions more cheaply and quickly. In both cases, therefore, the potential for human-machine collaboration is confirmed, with people imagining the most effective prompts to ask chatbots and proceeding iteratively to develop increasingly original solutions.

Some pioneers have been engaging their own communities by inviting them to use GenAI to brainstorm or co-create new campaigns and content. But the danger here lies in opening the door to malicious detractors who could ridicule the brand and cause hard-to-predict reputational damage. In 2016, for example, Microsoft launched Tay, an artificial intelligence-based chatbot designed to engage with Twitter users and learn from those interactions. Within hours, Tay began posting offensive and provocative tweets after being manipulated ad hoc by some users, forcing Microsoft to shut down the project and issue a public apology.

More generally, when thinking about new applications, it's useful to keep in mind the strengths of AI over human intelligence and vice versa. As noted above, AI currently excels at structured tasks that require mechanical and analytical skills (and it has the advantage of lower marginal costs), while humans are characterized by "contextual, intuitive, and feeling intelligence" (Huang and Rust, 2022). While newer AI systems are getting better at mimicking these latter abilities, it's often at the expense of output efficiency and transparency. In fact, several studies have suggested that prematurely deploying AI for critical tasks that are more in line with human capabilities can prove problematic. One example is price negotiation, a task that is not always structured and may require intuition and emotional intelligence. Indeed, in this context, Bertini and Koenigsberg (2021) rightly mention how dynamic pricing algorithms can lead to perhaps optimal decisions in the short term, but with long-term strategic costs related to negative customer perceptions of brand fairness, brand trust, and self-brand connection.

Marketing, by its very nature, deals with human behavior, relationships, and interactions; this means that personal sensibilities and tacit, heuristic knowledge are critical to its success (types of knowledge that are particularly difficult to transfer to AI models (De Bruyn et al., 2020)). For this reason, the widespread use of these technologies, particularly for more strategic decisions, may be overly ambitious compared to other business areas such as finance, information systems, or operations. On the other hand, for the automated execution of more structured tasks, and for support in less structured processes, the large-scale use of AI for marketing is only a question of when and how.

NOT JUST CO-PILOTING: THE REPLACE, ADD, AUGMENT MODEL

Now we need to build a bridge between the literature and field applications. The diagram in Figure 1 attempts to summarize, organize, and integrate the main considerations we've discussed so far to provide useful insights for management. With this representation, the *Replace, Add, Augment* model hones in on the macro-opportunities related to AI in marketing. The conceptual framework focuses on the possible trade-offs between cost efficiency and task effectiveness, keeping in mind that the ultimate goal of marketing is to find the best alignment between two priorities: value creation for the customer and value creation for the company. For the first, AI's ability to improve task effectiveness can play a key role; the second can benefit from the scaled-up efficiency provided by AI. The bidirectional arrows in the figure are a reminder that there is a continuum between the upper and lower parts of the model, with the implications becoming progressively more impactful at the extremes.

Replace

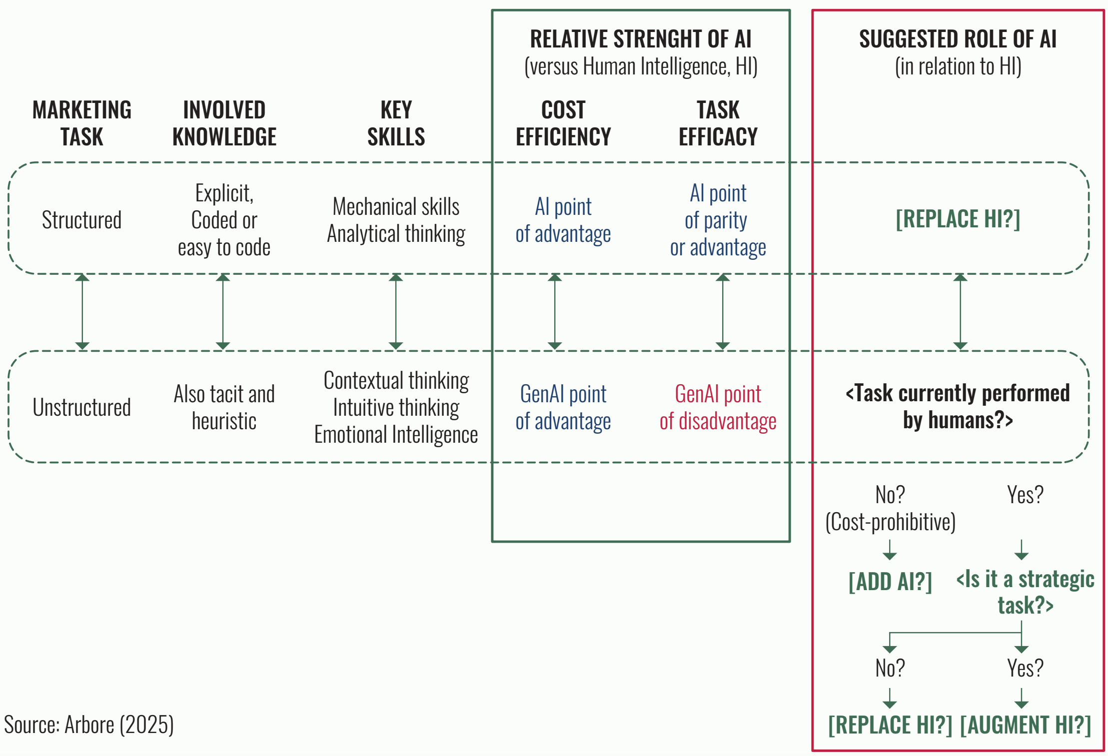
The replace option implies substituting human intelligence (HMI) with AI to fully automate a given marketing task. This choice would have to be evaluated under two main scenarios in which the competitive advantage of the early movers would be temporary, since in the long run it can be expected that all companies will adapt.

The first scenario concerns structured tasks with well-defined outputs, where there is explicit organizational knowledge to optimize. Unlike tacit knowledge (which is personal, contextual, and difficult to formalize), explicit knowledge is codified, documented and therefore easily transferable to machines. In addition, the more a task relies on analytical skills rather than emotional intelligence or intuition, the more it falls within the exclusive domain of AI (requiring little to no human intervention), thanks to both efficiency and effectiveness. An example we already mentioned is the use of algorithms to optimize the budget allocation for a SEM campaign, a process with short-term goals that are generally easy to code (e.g., optimizing a certain conversion rate) and predeterminable procedures for optimizing the outcome (e.g., A/B testing).

One compelling consideration, however, is that the question marks in Figure 1 (i.e., Replace?) are intended to discourage an excessively deterministic approach that would oversimplify the complexity of the real world. As one would expect, we've used the example of an SEM campaign. This is a task that's relatively structured, but not perfectly so. In fact, the lack of proper contextual understanding, i.e., a broader strategic vision, could lead to growth hacking tactics that are far too aggressive, and risk achieving suboptimal results in the long run. A typical case is ramping up clicks by sending an appealing but misleading message, which could undermine the brand's credibility or cause inconsistencies in its communication tone. Ultimately, the specific evaluation remains subjective: as they say in these cases, it's not so much the answers that matter, but the ability to frame the key questions correctly.

Next, there is a second case where AI should be considered to replace human intelligence altogether. We're talking about less structured tasks that are not critical to value creation. In such cases, AI may actually perform worse than humans, but the cost

FIGURE 1. THE POTENTIAL ROLE OF AI AND GENAI IN MARKETING PROCESSES: THE "REPLACE, ADD, AUGMENT" MODEL



Source: Arbore (2025)

and time advantages would outweigh the loss in effectiveness. Here, by definition, only GenAI or more advanced statistical models could take over, since it's precisely the unstructured tasks that require greater machine understanding of context and more than just mechanical reasoning skills. Therefore, given the lower quality guarantees, a full replacement of unstructured tasks is only conceivable for non-strategic processes. This assessment should also factor in the reputational and legal risks that could arise from the use of black-box algorithms: for example, any machine bias could inadvertently discriminate against some customers in favor of others, thereby damaging the brand image.

In addition to cost savings, the substitution process in these cases would also go a long way toward reducing the cognitive load and time consumed by human intelligence, so people could focus on tasks that are more critical to value creation. For example, some authors report how a banking institution is using generative AI to manage the constant flow of new financial market data. Arguably, a press review carefully performed by skilled professionals would produce superior results. In such situations, however, it may make sense to trade some quality for gains in speed and cost efficiency. In the example, the AI system replaces humans in the reporting processes by quickly processing and condensing multiple sources of information, such as annual reports and business analysis. This allows bank relationship managers to stay abreast of key market developments while freeing up time to better serve their contacts (Alavi and Westerman, 2023).

Add

Regarding the Add option of the model, we can refer to the previously reported examples of Expedia and Zalando, which have introduced new services and value drivers for their customers. These companies are using GenAI to address complex, unstructured tasks that were too expensive to offer in the past. Indeed, if a tour guide or personal stylist were to offer the same services, the result would certainly be more effective, but at a prohibitive cost. GenAI, on the other hand, makes it possible to enrich marketing value creation processes by introducing entirely new value drivers. Creative management can be particularly useful in rethinking the entire customer experience, analyzing each stage of the journey to identify new benefits or mitigate potential pain points, with a customized approach, in ways that were previously either technically infeasible or economically unsustainable.

Augment

This brings us to the final option, Augment, which is the one most often proposed in recent literature. In these cases, GenAI is introduced to enrich human intelligence (with all its biological limitations) to achieve meaningful goals by enhancing cognitive abilities, critical thinking, creativity, and knowledge sharing. However, some preliminary studies warn that GenAI support does not always improve the performance of knowledge workers (Dell'Acqua et al., 2023). For this to happen, these people must always be able to ignore any algorithmic suggestions that don't convince them, and they must be ultimately responsible for all outcomes. Ad hoc training and continuous monitoring of results are also useful.

An interesting example of the augment option in marketing (sometimes referred to as collaborative AI) comes from De Freitas and Ofek (2024). The authors describe the case of Nike, which contacted a number of artists specialized in developing innovative designs inspired by generative AI for the launch of new Air Max models. The team trained the algorithm on images of previous versions of Air Max and gradually refined the output to balance the level of novelty with Nike's distinctive style. They then brought together several ingredients - their own creativity, fashion expertise (tacit knowledge), knowledge of emerging trends, and Nike's specific marketing goals - to progressively drive the AI generative process and blend traditional brand elements with new colors, shapes, and patterns. The limited-edition sneakers resulting from this project sold out within days.

CONCLUSIONS

In the current evolutionary phase of marketing, it's more critical than ever to embark on a period of intense business exploration and rapid learning in this area. Rapid, but cautious: indeed, there's a great deal of uncertainty about both the opportunities associated with new AI trajectories and the costs, whether reputational, economic, or social. As De Bruyn (2020) rightly noted:

> *"In business in general and marketing in particular, there are too many 'unknown unknowns' [ossia cose che ancora non sappiamo di non sapere, ndr] to let AI algorithms, as effective and efficient as they may be in their day-to-day operations, function without human control and overriding capability."* (p. 100)

Not surprisingly, as noted above, investments in explainable AI are growing to level up human oversight. The goal is to reduce the trade-off that is well known to anyone involved in data modeling, namely between accuracy and interpretability of the result. (It's no coincidence that we also speak of *interpretable AI*.) Achieving a higher level of transparency opens the door to a better understanding of the logic behind algorithmic decisions. This is essential, especially in marketing, to identify and prevent dangerous errors or statistical biases with possible unintended discrimination. In this regard, Candelon et al. (2023) recall the case of Apple in the credit card market: in 2019, the company was severely criticized for a decision dictated by gender biases imported by its algorithm.[6] As mentioned above, the damage to the brand can be appreciable, even giving rise to legal implications. And since brand image can certainly not be subjected to A/B tests (since every action leaves a lasting impression), navigating the *unknown unknowns* requires particular circumspection.

However, with so much uncertainty and potential unknowns, we need to underscore that the biggest competitive risk today is delaying the start of a structured learning journey: *learn early, learn often*. As we've already mentioned, dealing with so much ambiguity requires an abductive marketing approach. According to this logic, the best decisions are made along the way, proactively beginning with assumptions and market views that are never fixed. It's an iterative path of discovery and refinement, but the approach must remain market-driving rather than market-driven: companies must explicitly define their assumptions and vision for AI, then progressively explore the best paths to their goal while continuously testing their assumptions. Hypotheses must be formulated and refined to best interpret the evidence at hand, combining insight with strategic ambition. Relentless testing and learning will be essential, starting the process as early as possible and monitoring progress frequently. Ultimately, execution will likely be the most complex and nuanced challenge in achieving success.

As a final consideration, we note that the widespread adoption of AI and data-driven tools is not yet standard practice for many companies. On the contrary, an AI divide may be emerging, widening the competitive gap between more sophisticated and more conservative organizations. But the good news is that it should no longer be financial resources that make the difference, but rather the willingness to innovate. From this point of view, many hope that GenAI and newer AI-based services can play a key role in helping even SMEs to compete with the largest companies, providing cost-effective capabilities that were once unimaginable, and in doing so leveling the playing field (Otis et al., 2023; Acar and Gvirts, 2024). Given the characteristics of the Italian business landscape, we can only hope that this is what will come to pass.

6 For more on the implications, including legal ones, see Clarke, 2019.

MANAGERIAL IMPACT FACTOR

- **Control and management of customer interactions**: The use of AI in chatbots may reduce the ability to control critical service interactions, escalating customer frustration when issues arise.
- **Customers and employee acceptance and trust in AI**: Algorithm aversion and perceived lack of transparency in black-box models can hinder AI adoption, requiring targeted communication strategies.
- **Balance between efficiency and strategic value**: Replacing human intelligence with AI is more effective for structured and repetitive tasks but can be risky for strategic undertakings that require insight and empathy.
- **Impact on creativity and business value**: Generative AI can support problem-solving and new product development, but overuse can lead to passive trend conforming rather than trend setting.
- **Reputational and legal risk management**: Implementing AI in marketing can expose companies to the risks of algorithmic bias, loss of public trust, and manipulation by malicious users.

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