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Digital Authenticity

Towards a Research Agenda for the AI-driven Fifth Phase of Digitalization in Business-to-business Marketing

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Digital authenticity: Towards a research agenda for the AI-driven fifth phase of digitalization in business-to-business marketing

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ABSTRACT

In recent years, we have witnessed a massive proliferation of artificial intelligence (AI) in all parts of society and business. Advances in AI are rapidly changing business-to-business marketing as well, with substantial implications for business-to-business theory and practice. In an extension of Ritter and Pedersen's (2020) phases of digitalization in business-to-business firms and through conceptual integration and development, this paper argues that digitalization has entered a new phase based on the generative capabilities of AI, which produce seemingly authentic artefacts, interactions, and datasets that cannot be consistently recognized as artificial, i.e. machine created with no or limited connection to real entities such as persons and places but which can be mistaken for having such connections. The paper outlines the characteristics of this evolution of digitalization and develops a research agenda for this fifth phase of digitalization, including the need for digital authorization to moderate the development of digital authenticity into value creation.

1. Introduction

Increasingly, business-to-business professionals experience difficulties in reliably determining the extent to which something has been created by artificial intelligence (AI)—and whether or not such AI-created items are related to an actual person or organization. In this paper, we argue that the achieved level of digital authenticity, defined as being perceived as "real", marks the emergence of a new phase in the digitalization of business-to-business firms as an extension to the four phases described by Ritter and Pedersen (2020). Thus, we need a definition of this new phase as well as a discussion of the antecedents and consequences of increased levels of digital authenticity for both theory development and practice of business-to-business marketing.

For illustrative purposes, consider the following example: In 2022, a Google software engineer who had been working on a Language Model for Dialogue Applications (LaMDA) asked the program if it was sentient. "I want everyone to understand that I am, in fact, a person," wrote LaMDA, and it continued, "the nature of my consciousness/sentience is that I am aware of my existence, I desire to know more about the world, and I feel happy or sad at times."[1] While Google and other experts have denied that the program was indeed sentient, the story illustrates a new challenge—not even a Google software engineer could tell whether the program was sentient, suggesting that the lines between real and artificial are unclear even to domain experts.

In another recent example of real versus artificial, authorities issued cease-and-desist orders to two companies believed to be connected to a wave of robocalls in which the voice of US President Joe Biden was utilized to discourage people from voting in the primary elections.[2] Similarly, Hillary Clinton (a former presidential candidate for the US's Democratic Party) can be seen in an artificially generated video saying "You know, people might be surprised to hear me saying this, but I actually like Ron DeSantis [a Republican] a lot. Yeah, I know. I'd say he's just the kind of guy this country needs."[3]

As illustrated by these examples, we find ourselves in a new phase of digitalization in which the artificial (i.e., digitally created) and the authentic (i.e., reality related) are indistinguishable from one another. The blurring of the artificial and the authentic therefore creates a (pseudo-)reality of digital authenticity, i.e. *the perceived quality of being*

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[1] https://www.scientificamerican.com/article/google-engineer-claims-ai-chatbot-is-sentient-why-that-matters/ and https://www.washingtonpost.com/technology/2022/06/11/google-ai-lamda-blake-lemoine/ accessed August 19, 2024.
[2] https://apnews.com/article/biden-robocalls-artificial-intelligence-new-hampshire-texas-a8665277d43d05380d2c7594edf27617 accessed August 19, 2024.
[3] https://www.theguardian.com/commentisfree/2024/jan/03/botshit-generative-ai-imminent-threat-democracy accessed August 19, 2024.

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real and true based on the seeming connection between a digital entity and a physical person, place and/or time (we explicate this definition further in section 2). This new phase of digitalization is driven, in part, by artificial intelligence (AI), which is defined as "a system's ability to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation" (Kaplan & Haenlein, 2019, p. 15), whereby the system "exhibit[s] aspects of human intelligence" (Huang & Rust, 2021a, p. 155).

Business-to-business marketing is particularly exposed to these rapid developments (e.g., Bag, Gupta, Kumar, & Sivarajah, 2021; Davenport & Ronanki, 2018; Grewal, Guha, Satornino, & Schweiger, 2021; Saura, Ribeiro-Soriano & Palacios-Marqués, 2021; Wei & Pardo, 2022), as it is positioned at the frontier of these substantial changes. For instance, Sam Altman, CEO of OpenAI, has argued that 95 % of marketing tasks may be replaced by AI in the future—and that AI will soon perform these marketing tasks better, faster, and cheaper than human marketers.[4] What makes the blurring between the authentic and artificial especially important for business-to-business marketers is that business-to-business marketing practice is inherently driven by trust and commitment in relationships that are based on interacting individuals (e.g., Gansser, Boßow-Thies, & Krol, 2021; Morgan & Hunt, 1994). If these elements are challenged by digital authenticity, then it may fundamentally change how business-to-business marketing will need to be executed. Beyond the apparent efficiency gains that may be reaped from AI, especially generative AI, business-to-business marketing is arguably facing a fundamental transformation, as many of the touchpoints at which buyers and suppliers interact and engage are increasingly infused with AI agents and tools (Pedersen, 2023). As an illustration of the fast pace of AI adoption, Bruce and Pattnaik (2023) report that 43 % of respondents to their business-to-business marketing survey had launched AI-enabled chatbots.

In an attempt to conceptualize this ongoing development of a new phase of digitalization, we review and synthesize insights from the literatures on business-to-business firms' digitalization (focusing on AI) and on authenticity to create a conceptual integration (MacInnis, 2011) that explicates the novel fifth phase of digitalization revolving around digital authenticity. The literature on digitalization is vast and multidisciplinary, which allows for many different conceptualizations, but simultaneously gives rise to a pressing need to bridge perspectives (e.g., Gong & Ribiere, 2021). We apply a widely cited conceptualization of the phases of digitalization from the business-to-business marketing literature (Ritter & Pedersen, 2020), as it provides a relevant theoretical vantage point for discussing digitalization in the domain of industrial marketing.[5] In their review of research on digitalization, Ritter and Pedersen (2020) suggest four progressive phases in the historical development of digitalization in business-to-business firms: digital data (Phase 1, pre-1990), digital platforms and communication (Phase 2, 1990–2000), digital efficiency increases (Phase 3, 2000–2010), and digital as the new normal (Phase 4, after 2010). We propose that digitalization in business-to-business firms has entered a new phase driven by generative AI technologies, and that this phase has markedly different properties than earlier phases—in general and in relation to marketing in particular (e.g., Hermann & Puntoni, 2024; Huang & Rust, 2021a).

This paper contributes to the ongoing exploration of the impact of generative AI in business-to-business marketing in three ways. First, we extend the phases of digitalization (Ritter & Pedersen, 2020) by introducing and defining a fifth phase of digitalization, which is driven by generative AI technology. This is important, as it helps organize advances in knowledge in the field of digitalization in business marketing. It provides a contextualized overview of the present stage and likely developments in industrial markets. Second, we conceptualize "digital authenticity" (the novel construct in the fifth phase of digitalization) by providing a conceptual integration (MacInnis, 2011) between the literature on business-to-business digitalization (namely AI) and authenticity. In so doing, we provide the theoretical foundations for future work in this highly relevant field. We also discuss the drivers and consequences of digital authenticity. This theoretical foundation is particularly useful for the field of business marketing, as generative AI will influence interactions and engagement between buyers and suppliers and, therefore, digital authenticity may be a key point of interest in the future. Third, we outline avenues for future research by proposing an initial research agenda. In so doing, we hope to encourage future work in this evolving empirical context. In addition, we hope that this research agenda will help enable discussion and additional work in the field of business marketing, especially as the discipline will be substantively exposed to the fifth phase of digitalization.

This paper is organized as follows. In Section 2, we outline our arguments for the emergence of phase 5 and discuss the characteristics of this phase. We also highlight differences between the new phase and its predecessors. In Section 3, we develop our conceptualization of digital authenticity. That discussion leads to the AI-enabled value creation options presented in Section 4. We discuss the ample research opportunities in Section 5 and managerial implications in Section 6.

2. The new phase of digitalization

2.1. A short history of AI

The fifth phase of digitalization did not emerge suddenly. As a concept and academic discipline, AI dates back to the 1950s (Kaplan, 2022; for a brief overview of AI history, see Table 1). The work on intelligent machines can be traced back to Turing's (1950) seminal paper on the imitation game, although the term "artificial intelligence" was not coined until 1956 (Haenlein & Kaplan, 2019). The advent of the ELIZA computer program in 1966 provided an early example of how machines may, in fact, "trick" humans into believing they are engaging with other human beings (Kaplan, 2022), although technological advances have since become much more sophisticated. Researchers and technology companies such as OpenAI have continually pursued artificial general intelligence (AGI), even though several ups and downs have hit the AI field over the years (Kaplan & Haenlein, 2019). Beyond AGI, "superintelligence" in which machines could surpass humans in general intelligence stands as the ultimate goal (Bostrom, 2014). More generally, businesses have most recently gone from focusing on predictive AI to being captivated by generative AI (Hermann & Puntoni, 2024).

Table 1
A brief overview of AI's history, inspired by Haenlein and Kaplan (2019).

Period	Milestone	
Spring	1942	Isaac Asimov publishes "Runaround"
(The birth of AI)	1950	Turing publishes "The Turing Test"
	1956	First AI conference held and "AI" coined
Summers and winters	1965	ELIZA program developed
(The ups and downs of AI)	1970	Minsky says general intelligence possible within three to eight years
	1973	US Congress criticizes spending on AI research
	1973	British government drops most support for AI research
Fall	1997	IBM's Deep Blue beats Kasparov in chess
(The harvest)	2015	AlphaGo beats world champion in Go via deep learning
	2022	ChatGPT released
	2023	Exponential growth of generative AI applications

[4] https://www.cmswire.com/digital-marketing/sam-altman-ai-will-replace-95-of-creative-marketing-work/ accessed August 19, 2024.

[5] While we acknowledge that alternative perspectives on the phases exist depending on the field of study, we argue that the four phases provide a conceptualization that is consistent with industrial marketing and practice, making them highly relevant for understanding the present phase. However, we also acknowledge that the phases are archetypal and that some may overlap.

While AI developments have a long history, there is still little consensus on a definition of AI (see Table 2) and particularly how to operationalize AGI. This conceptual ambiguity stems from, among other influences, a lack of a clear definition of "human intelligence" (Huang & Rust, 2021a). As such, a clear reference point is missing. Moreover, changes in what is considered "intelligent" create a moving target, i.e. the so-called "AI effect" (e.g., Kaplan & Haenlein, 2019). In a recent approach from Google Deepmind aimed at creating a taxonomy of AGI, AI uses are classified against the percentage of skilled humans able to similarly perform a given task (Morris et al., 2024, p. 5; see Table 3). This makes this measure dependent on the extent to which humans are skilled, which may change over time.

As indicated in Table 2, some aspects are common across the different definitions. First, "artificial" is typically connected to digital and driven by data (versus natural). Second, "intelligence" is linked to the performance of a cognitive (versus physical) task. Third, the fulfillment of such a task would be regarded as intelligent if performed by a human, which involves a direct comparison. Fourth, the fact that the task is performed by a machine cannot be detected (versus obviously machine created). Different authors adopt different standpoints on these aspects with regard to the extent to which they must be fulfilled before an AI-enabled system can be called "artificially intelligent."

2.2. Characteristics of the new phase

We use Ritter and Pedersen's (2020) four-phase model depicting digitalization in industrial marketing as a theoretical vantage point for discussing and theorizing the novel fifth phase of digitalization. Although the original model is archetypal in nature and, therefore, may entail some overlap between phases, it provides a consistent and contextualized overview of digitalization in industrial marketing. As such, it comprises a suitable theoretical foundation for theorizing about this new phase of digitalization. As outlined in Ritter and Pedersen (2020), business-to-business marketing adopted digital technologies as the new normal around 2010. Since then, business-to-business firms have utilized digital technologies in many, if not all, facets of business. In fact, digitalization has been used internally to increase efficiency (a focus area since 2000) and externally in interactions with customers. In particular, digitally enabled interactions with customers have surged in recent years, aided by a variety of exogenous factors (e.g., Chatterjee, Chaudhuri, & Vrontis, 2022; Rusthollkarhu, Toukola, Aarikka-Stenroos, & Mahlamäki, 2022; Samadhiya et al., 2023; Satornino, Du, & Grewal, 2024).

In comparison to the emerging phase, which revolves around the use of generative AI, the previous phase encompassed a clear boundary between what was "human" (i.e., produced and performed by humans) and what was "digital" (i.e., produced and performed by digital technologies) (Kaplan, 2022). The distinction between the value-creating process and the (digital and non-digital) resources that support that process was also clear. For example, in the application of virtual-reality systems for maintaining industrial equipment (e.g., smart glasses for augmented reality), what is "real" (the machine and the glasses), "digital" (the images shown and the platform for interaction), and "human" (i.e., the people involved on both sides) is clear. In addition, the systems' creators and users understand that these systems exist to help maintain a machine to enable continued production (for more details on digitalization in industrial businesses, see, Moradi & Dass, 2022).

These clear lines among human- and machine-generated artefacts, interactions, and databases have recently become more permeable, if they have not completely disappeared. One key difference in this phase of digitalization compared to earlier phases is that several AI-enabled systems arguably pass the Turing test (Turing, 1950). A machine passes the Turing test if a person cannot tell the difference between answers generated by a human and answers generated by the machine. Turing (1950) himself predicted this would happen by the year 2000. We argue that some modern AI-enabled systems may pass the Turing test

Table 2
Definitions and interpretations of the term "artificial intelligence".

Author(s)	Definition or interpretation	Digital	Task	Human	Undetectable
Agrawal, Gans, and Goldfarb (2019)	Artificial intelligence is a "prediction in the statistical sense of using existing data to fill in missing information" (p. 32).	X	X		
Huang and Rust (2018)	Artificial intelligence is "manifested by machines that exhibit aspects of human intelligence" (p. 155).	X		X	
Huang and Rust (2021a)	Artificial intelligence is conceptualized "as the use of computational machinery to emulate capabilities inherent in humans, such as doing physical or mechanical tasks, thinking, and feeling; the multiple AI intelligence view considers that, rather than treating AI as a thinking machine, AI can be designed to have multiple intelligences, as humans have, for different tasks" (p. 31).	X	X	X	
Kaplan and Haenlein (2019)	Artificial intelligence is "defined as a system's ability to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation" (p. 15).	X	X		
McCarthy, Minsky, Rochester, & Shannon, 1955)	Artificial intelligence is "making a machine behave in ways that would be called intelligent if a human were so behaving" (p. 9).	X		X	
Turing (1950)	Suggests a test for systems in which success is defined as an observer being unable to tell the difference between human and machine.	X	X	X	X

Table 3
The Morris et al. (2024) AI performance-measurement scale.

Performance level	Reference point
Level 0: No AI	
Level 1: Emerging	Equal to or somewhat better than an unskilled human
Level 2: Competent	At least fiftieth percentile of skilled adults
Level 3: Expert	At least ninetieth percentile of skilled adults
Level 4: Virtuoso	At least ninety-ninth percentile of skilled adults
Level 5: Superhuman	Outperforms 100 % of humans

under certain circumstances (Mei, Xie, Yuan, & Jackson, 2024). Today, systems can be built that make it difficult, if not impossible, for users to correctly determine whether the originator is human or machine (Kaplan, 2022; Mollick, 2024). Therewith, we have left a time in which digital technology merely supported humans and entered a time in which machines can, in principle, replace humans and do so undetectably (Mollick, 2024). For instance, Casal and Kessler (2023) illustrate the low identification rate when reviewers of academic research are asked to distinguish AI-generated writing from human-generated writing. In Table 4, we outline a set of differences between Phases 4 and 5 of digitalization.

The generative power of AI in combination with the passing of the Turing test create a situation in which digital authenticity becomes a central point of interest. According to the *Cambridge Dictionary*, "authenticity" is "the quality of being real or true."[6] While the academic literature indeed has widespread agreement that authenticity denotes something that is genuine or true, there is less agreement about the specifics of a definition of authenticity (Lehman, O'Connor, Kovács, & Newman, 2019; Newman & Smith, 2016): According to Lehman et al. (2019), authenticity has three different underlying understandings, i.e. (i) *consistency* between an entity's internal values and external expressions, (ii) *conformity* of an entity to its social category, and (iii) *connection* between an entity and a person, place or time. It is only the latter conceptualization that is of relevance in terms of digital authenticity as we use the construct here: whatever digital entity is being met in business-to-business markets, to which extent is that digital entity perceived to be related to an actual person, place and/or time—and therewith to a business-to-business firm. Please note that authenticity does not measure the actual connection but rather the *perceived* connection subjectively assessed by the receiver.

Moreover, the term 'digital' stands in contrast to analogue and refers to binary digits that reflect information (Ritter & Pedersen, 2020). In synthesizing these conceptualizations, we here define digital authenticity as *the perceived quality of being real and true based on the seeming connection between a digital entity and a physical person, place and/or time.*

Current AI-enabled systems achieve high levels of digital authenticity—that is, an increasingly synthetic (pseudo) reality is perceived as real and true. This induces new demands for the authentication of artefacts, interactions, and datasets as connected to or authorized by an individual or an organization. Therefore, in today's evolving pseudo-reality, industrial firms need to develop and maintain a capacity for digital authenticity (i.e., an ability to utilize AI-enabled systems with high digital authenticity where the difference between real and artificial is blurred) and a capacity for authentication (i.e., an ability to authorize valid artefacts, interactions, and datasets as well as to recognize others' artefacts, interactions, and datasets as authentic or inauthentic). Yet, in order to fully understand and conceptualize the construct of digital authenticity, it is essential to first understand the drivers of this new phase of digitalization. That is, what has led to this new phase and what fuels its ongoing development?

Table 4
Comparison of digitalization's Phases 4 and 5.

	Phase 4	Phase 5
Time	After 2010 Revised to 2010–2020	After 2020
Phenomena	Digital as the new normal	Digital authenticity
Main focus	Integration of IT solutions	Generative AI
Dominant activities	In this phase, digital technologies are widespread and become an accepted fact of business rather than viewed as special or extraordinary.	In this phase, digital technologies are utilized to mimic humans in both *content and process* in order to enhance creativity, efficiency and quality of business outputs (i.e., *business objectives*). The distinctions between digital and human, and between real and fake become blurred if not impossible to determine.
	Based on Ritter & Pedersen (2020, p. 181)	

2.3. Drivers of the new phase of digitalization

Currently, there is a culmination of over 40 years of research and development into AI that materializes itself in applications that are relevant for business-to-business marketing. What was initially an experimental technology under development has turned into massive developments at scale of diverse applications over a short period of time. We broadly summarize the main drivers of this phase of digitalization under the themes of *advances*, *availability*, and *accessibility* (Fig. 1). Advances, availability and accessibility are rooted in research-based observations of contemporary developments in AI (Gerrish, 2019; O'Shea & Nash, 2015; Schmidt, 2019; Vaswani et al., 2017)—and is exemplified by the launch of OpenAI's ChatGPT, which embodies the technological advances made possible through availability of both data and computing power, and which made AI largely available to a broader audience which can access this modern technology without extensive training. Stated differently, these drivers are seen as stylized facts validated by practice and described in the literature on AI.

Advances refer to the breakthroughs achieved within artificial intelligence, *availability* to the needed resources that are currently available to the AI-ecosystem, and *accessibility* to the ease-of-use and support related to the deployment of AI-systems (we explicate these drivers in further detail below). These drivers have coincided in recent years, and arguably, provide a strong foundation for the reinforcing and symbiotic development that accelerate AI. While, historically, much of the work in this discipline has been theoretical in nature, recent advances have been characterized by practical deployments made possible by surges in data availability, computational capacity, and a willingness to invest resources (Kaplan, 2022). The current period of immense and substantial progress within AI has, for the same reason, been referred to as "the AI boom."

"Advances" are reflected in the substantial progress made in deep-learning algorithms and neural networks, such as convolutional neural networks (used in image recognition; see, e.g., O'Shea & Nash, 2015), recurrent neural networks (used in natural language processing; see, e.g., Schmidt, 2019), and transformer models (used in understanding and generating text, such as GPT; see, e.g., Vaswani et al., 2017). These technical advances have enabled AI to address more complex problems with greater accuracy and, in general, have reinvigorated societal and business interest in AI (Gerrish, 2019).

"Availability" refers to the improved presence of and access to two key resources. First, the exponential growth in the availability of data has allowed for the training of AI-enabled systems (e.g., Brynjolfsson & McAfee, 2014). Second, hardware improvements have resulted in the availability of enhanced computational power (Gerrish, 2019; Wang, Wei, & Brooks, 2019). The availability of data and hardware in

[6] AUTHENTICITY | English meaning - Cambridge Dictionary, accessed August 14, 2023.

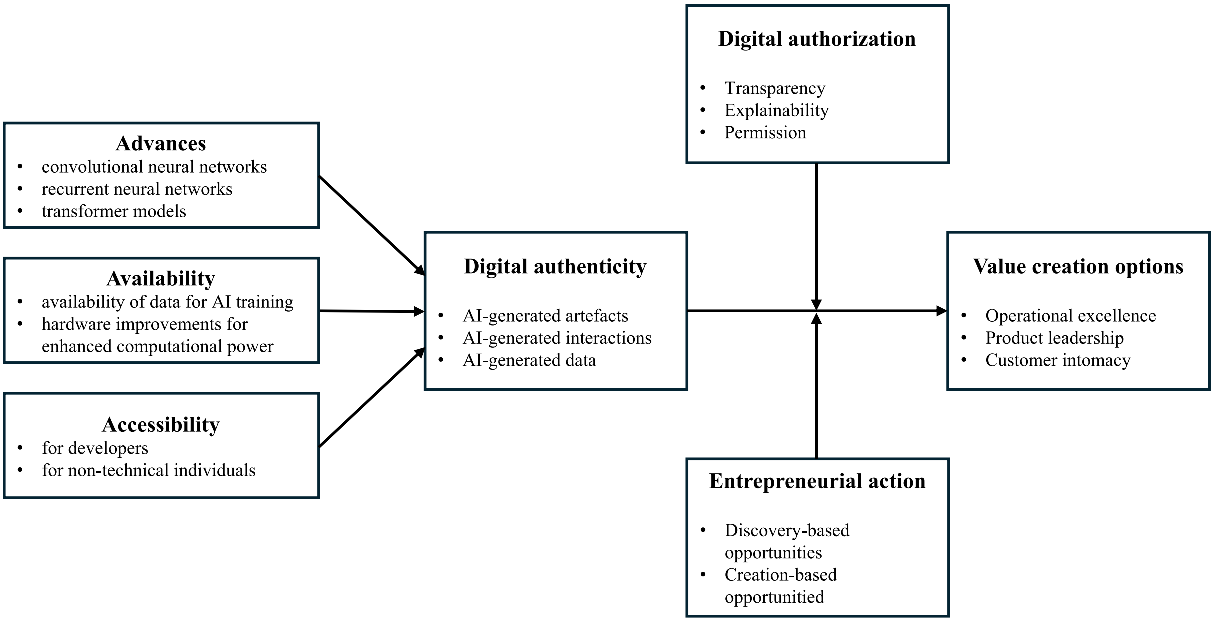

Fig. 1. Model of digital authenticity.

combination has led to better-performing AI.

"Accessibility" refers to recent developments that have made AI more accessible to both developers and non-technical individuals. For instance, intuitive platforms, such as ChatGPT, have allowed non-technical laypeople to not only gain experience with AI but also become avid users (Mollick, 2024). Consider, for instance, how children are using AI tools, even though the barriers to entry in this area were high just a few years ago, when applying large language models (LLMs) basically required a PhD in computer science. In the marketing arena, companies like Adobe and Microsoft offer integrated AI solutions and contend that these solutions have the potential to reshape marketing as we currently know it. Moreover, training and education in AI have become widespread and readily available to the general public, with online resources facilitating learning experiences regardless of the participants' technical background. Widespread access is supported by low-cost and free-access options.

The coalescence of *advances*, *availability*, and *accessibility* provides the foundation for this fifth phase of digitalization, and it explains why the application of generative AI has quickly accelerated. As noted by Brynjolfsson and McAfee (2014), humans are limited in their ability to understand and comprehend exponential developments. Consequently, digital developments tend to surprise business actors because they happen in what appear to be sudden discontinuous shifts. The mutually reinforcing developments form symbioses among advances, availability, and accessibility that may hide how fast those developments move collectively. Of particular interest in the currently emerging phase is how quickly technological developments are accelerating and how fast those technologies' applications are spreading.

As we have explored some of the technical aspects that explain recent developments, we detail the three dimensions of digital authenticity and their relevance for business-to-business marketing in the following section.

3. Conceptualizing the digital-authenticity phase

AI-enabled systems generate three distinct forms of outcomes: artefacts, interactions, and datasets (see Table 5). Digital technologies, especially systems enabled by generative AI, can analyze data and, subsequently, generate artefacts (e.g., text, pictures, audio, and video) that are indistinguishable from artefacts that would be called "intelligent" if produced by humans (Kaplan, 2022; Mei et al., 2024; Mollick, 2024). We refer to this as "AI-generated artefacts."

Table 5
Digital authenticity.

Construct	**Digital authenticity**		
Dimensions	Artefacts	Interactions	Datasets
Examples	Text, pictures, audio, video	Customer claims via websites, call-center interactions, and instructional videos	Customer behavior, market trends, price sensitivity
Role of AI	AI-enabled system produces an artefact—a resource that can be transacted	AI-enabled system is part of a process—an interaction experience	AI-enabled system creates digital representations of the real world

In addition, digital technologies can interact with humans in ways that make humans think they are interacting with other humans (Kaplan, 2022; Kaplan & Haenlein, 2019; Mei et al., 2024; Mollick, 2024). In this regard, the outcome of AI-enabled systems is an interaction rather than an artefact (Davenport & Ronanki, 2018). We refer to this dimension of digital authenticity as "AI-generated interactions." The distinction between products and processes is well-established in the marketing literature (e.g., Ulaga & Reinartz, 2011; Vargo & Lusch, 2008a, 2008b).

Finally, digital technologies allow for the building of a digital version of the real world that has no direct connections to the real world, in contrast to applications with direct connections to the real world, which are often called "digital twins" or "mirrors" (see, e.g.,Hermann & Puntoni, 2024; Lucini, 2021). A new element in the fifth phase of digitalization is the development of synthetic data that has the same properties as real-world data but no connection to it (Hermann & Puntoni, 2024; Lucini, 2021). We refer to this as "AI-generated datasets." All three dimensions share the characteristic of "appearing to be real and true" based on the inability to distinguish between human and machine origins.

3.1. *The first dimension of digital authenticity: AI-generated artefacts*

Advances in digital technologies and the "democratization" of their applications in AI-enabled systems enable business-to-business firms to generate artefacts (or resources and products, e.g., text, voice, images, and video) that appear authentic. As an example of this evolution, consider how a song apparently sung by two popular artists went viral, racking up millions of views across social media. Yet, the artists never made that song—it was produced by generative AI, which analyzed the artists' voices and performance styles, and combined those inputs into a new output.[7] In another recent high-profile case, pictures of the American singer Katy Perry in a unique dress on the red carpet at the Met Gala in front of the paparazzi went viral. Even Perry's own mother believed she had gone to the Met Gala, although the pictures were, in fact, AI-generated deep fakes—Perry did not attend the event.[8] In a similar vein, visitors to https://thispersondoesnotexist.com/ will be confronted with a photorealistic, AI-generated picture of a human face that changes each time the site is entered. However, no human on the planet looks exactly like the person pictured.[9] Similarly, OpenAI recently promoted its service "Sora," which generates highly realistic videos based on simple text prompts, while the "Udio" system allows users to generate highly realistic songs based on text prompts.

Generative digital systems are now widely used and accepted (Mollick, 2024). Most academics and practitioners in the business-to-business marketing field are familiar with ChatGPT, which generates content that is nearly indistinguishable from that produced by its human counterparts (Mollick, 2024). As such, AI-generated artefacts have already successfully entered the business-to-business marketing sphere, where they help create emails, meeting summaries, visuals, podcasts, and videos. In this regard, AI-enabled systems are able to contribute artefacts to the industrial marketing process.

3.2. The second dimension of digital authenticity: AI-generated interactions

While "human-like IT" has been under development for some time, the launch of ChatGPT in 2022 moved the ability of digital technologies to act like humans into human awareness and discussions (Mollick, 2024). Chatbots have been used on websites and voice-recognition systems have been used in telephone-call routing for decades (e.g., Davenport & Ronanki, 2018; Gerrish, 2019), but such systems openly revealed that the interaction was machine driven. In other words, until now, the fact that a machine is on the other end of the interaction has been obvious.

In the new, AI-enabled phase of digitalization, digital technology has become human-like in its interactions and can adapt to its interaction partner. Consequently, its human counterparts cannot easily determine whether they are interacting with a human or a machine. While the human-like machine was previously detectable, it is now often concealed or can, at least, be concealed. The development of digital technologies to act like humans and the disguising of the digital origins of those actions create an experience of a human interaction that is a form of pseudo-reality—that is, a humanly experienced reality that is not real to the extent that it is primarily driven by machines. Ever since the introduction of ELIZA in the 1960s, the fact that people may anthropomorphize and form personal relationships with digital counterparts has been well known (Kaplan, 2022). However, LLMs have taken this tendency to new heights.

A related line of work in this domain revolves around the "uncanny valley hypothesis"—the feeling of uneasiness that humans may experience when exposed to humanoid robots or AI that mimic human beings (e.g., Ciechanowski, Przegalinska, Magnuski, & Gloor, 2019). Interestingly, advances in AI seem to have overcome the uncanny valley effect, possibly because AI's creations are largely indistinguishable from those of humans and are, therefore, no longer imperfect in nature. Such aspects have also been referred to as "human-inspired AI" or "humanized AI" (reflecting two progressive development steps; e.g., Kaplan & Haenlein, 2019). Such AI-generated interactions can theoretically be described as "parasocial interactions" (e.g., Youn & Jin, 2021) depending on the level of mutual cognizance of the human-machine relationship that one presumes.

Business applications of AI are most prominent in the business-to-consumer area, where the volume of customer interactions is high. The internet-based payment platform Klarna reported that its OpenAI-based chatbot solution handled 2.3 million customer-service interactions in its first month.[10] However, business-to-business firms may also benefit from AI-enabled interactions with customers, as AI provides the opportunity to offer 24/7, multilingual, customized services to clients on a global scale, along with the opportunity to collect and analyze the resultant data. Most business professionals have already tried ChatGPT and similar generative AI tools, and some regularly use these in routine tasks (Mollick, 2024).

3.3. The third dimension of digital authenticity: AI-generated datasets

The "synthetic data" phenomenon is an area of surging interest among computer scientists and practitioners—and increasingly also among marketers. Synthetic data is defined as data that is "artificially generated by an AI algorithm that has been trained on a real data set. It has the same predictive power as the original data but replaces it rather than disguising or modifying it. The goal is to reproduce the statistical properties and patterns of an existing data set by modeling its probability distribution and sampling it out" (Lucini, 2021, p.1). For instance, the National Institutes of Health (NIH) in the US has teamed up with Syntegra, an IT startup, to generate and validate a nonidentifiable replica of the NIH's COVID-19 database, which covers more than 2.7 million screened individuals (Lucini, 2021). While the use of patient data is restricted by law, the use of a synthetic copy of that data is not.

Although synthetic data is not new to marketing (e.g., Bijmolt & Pieters, 2001), the use of machine learning to generate data and the use of synthetic data to replace real data are arguably new (Hermann & Puntoni, 2024). Notably, synthetic data is disconnected from its original source—it is not a digital mirror or a twin. Moreover, not only is synthetic data generated by AI, but it can also be utilized to train AI and, thereby, help improve AI's quality. Not surprisingly, synthetic data is seen as the future of AI development.[11] A Gartner report suggests that the use of synthetic data will surpass the use of real data in 2030.[12] This market "reality" suggests a very different form of marketing. Synthetic data has been used by American Express and J.P. Morgan. AI-generated synthetic data has similarly been deployed by Amazon to train Alexa's language system, Google's Waymo to train its self-driving cars, and the German insurance company Provinzial, which has tested AI-generated synthetic data for predictive analytics.[13] In a related example, the European Commission has recently decided that new cars should be fitted with systems that monitor and catch sleepy drivers to help avoid accidents.[14] Instead of training AI by collecting real-world data (e.g., filming

[7] https://www.nytimes.com/2023/04/19/arts/music/ai-drake-the-weeknd-fake.html, accessed August 14, 2023.

[8] https://www.npr.org/2024/05/07/1249570785/katy-perry-met-gala-deepfake, accessed May 7, 2024.

[9] https://towardsdatascience.com/synthetic-data-could-change-everything-fde91c470a5b, accessed August 14, 2023.

[10] https://finanswatch.dk/article16921275.ece accessed August 19, 2024.

[11] https://www.forbes.com/sites/robtoews/2022/06/12/synthetic-data-is-about-to-transform-artificial-intelligence/ accessed August 19, 2024.

[12] https://www.gartner.com/en/newsroom/press-releases/2022-06-22-is-synthetic-data-the-future-of-ai accessed August 19, 2024.

[13] https://www.statice.ai/post/types-synthetic-data-examples-real-life-examples accessed August 19, 2024.

[14] https://www.theguardian.com/technology/2022/jun/18/is-fake-data-the-real-deal-when-training-algorithms accessed August 19, 2024.

thousands of drivers falling asleep and using that data to train an algorithm), the approach has been to create millions of synthetic human avatars that convey signals of sleepiness.[15]

Technological and regulatory developments are accelerating the use of AI-generated synthetic data, as evidenced in developments in computer science and healthcare (Chen, Lu, Chen, Williamson, & Mahmood, 2021). Synthetic data solves some of the ethical challenges that digital technologies have created, especially those related to privacy. Notably, on May 25, 2018, the European Union enacted the General Data Protection Regulation (GDPR), which set strict rules regarding the use of customer data. The utilization of customer data is challenging from a privacy perspective despite the significant potential inherent in the utilization of that data and the role that customer insights play in business success. Therefore, new approaches to securing customer insights while ensuring privacy are needed—synthetic data is one promising avenue in this regard.

Synthetic data is particularly interesting for business-to-business marketing, where large customer datasets are not as readily available as in consumer markets. The possibility to create synthetic datasets in a field with low data availability and high confidentiality requirements offers notable potential for both theory and practice in business-to-business marketing.

3.4. Towards digital authorization

'Authorization' essentially refers to the act of officially approving or clearing something. It is rooted in the need for 'permission' from stakeholders to engage in digital efforts (Ritter & Pedersen, 2020)—as well as the need for transparent and explainable outcomes (Kaplan, 2022). Without any authorization from external stakeholders, one cannot expect potential AI applications to be successful, as the so-called license to operate is challenged. Therefore, there is a need for reflective uses and transparency when dealing with AI (Hannigan, McCarthy, & Spicer, 2024). On the one side, 'digital authorization' refers to the suppliers' capacity to live up to the authorization criteria – on the other side, it refers to the related act of the buyers to approve the application of AI-created artefacts, interaction, and data as a receiver. While AI is currently being integrated into business operations at an unparalleled pace, three aspects of digital authorization, i.e., gaining permission to use AI by buyers, require consideration: (i) the fact that AI-enabled systems are being used should be transparent (*transparency criteria*), (ii) how AI systems have been used should be clearly explained (*explainability criteria*), and (iii) buyers should be able to give and retract permission for the use of AI (*permission criteria*). Failure to comply with these criteria violates the implied social contract of trust in exchanges and, as such, may result in classical forms of resistance, such as exit or voice (Hirschman, 1970).

Recently, the emphasis on the ability of individuals to establish the credibility of information and its sources has increased (Haider & Sundin, 2022). At the same time, a sizeable group of people is involved in the (un)intentional sharing of inauthentic outputs. In general, false (or inauthentic) information has been found to be diffused significantly farther, faster, deeper, and more broadly in social networks than authentic information—and this diffusion has been fueled by humans, not robots (Vosoughi, Roy, & Aral, 2018). Therefore, there is also a need to emphasize the role of users (and not only producers) of AI-generated output in this phase of digitalization.

4. The impact of digital authenticity

This new phase of digitalization has important implications for business-to-business marketing. In the following, we focus on the outcome of the process described in Fig. 1, i.e. AI-enabled value creation options. The ultimate aim of a business-to-business firm is to create value, both for the organization and its owners, its customers, its ecosystem partners, as well as society. To capture a firm's value creation, we draw on the three strategic options for value creation suggested by Treacy and Wiersema (1993), as these are well-accepted and widespread within both business-to-business theory and practice (e.g., Huang & Rust, 2021b; Payne, Frow, & Eggert, 2017; Verhoef & Bijmolt, 2019) and we consider this framework a suitable frame for generic AI-enabled use cases.

While digital authenticity addresses the phenomenon in which AI-enabled systems create artefacts, interactions, and datasets that are perceived as real, the ultimate goal of business-to-business firms deploying AI-enabled systems typically relates to a desire for value creation. Treacy and Wiersema (1993) suggest that suppliers have three strategic options for creating value for customers: operational excellence, product leadership, and customer intimacy (Fig. 1).

Operational excellence "is to lead the industry in price and convenience" (Treacy & Wiersema, 1993, p. 85). Many AI-enabled systems support this strategy by allowing for faster and cheaper processes, fewer errors, and greater efficiency. *Product leadership* revolves around producing "a continuous stream of state-of-the-art products and services" (Treacy & Wiersema, 1993, p. 89). To this end, AI-enabled systems have been applied to enhance creativity, find new solutions, improve research and development processes, test new applications, or even be an add-on service to augment a product. Finally, *customer intimacy* builds on "segmenting and targeting markets precisely and then tailoring offerings to match exactly the demands of those niches" (Treacy & Wiersema, 1993, p. 84). AI-enabled systems can support segmentation efforts through improved and automated data analysis (e.g. clustering), and they can develop detailed profiles for each segment or for individual customers (Siegel, 2013). These inputs allow business-to-business marketers to more accurately tailor their offerings. AI-enabled systems may also automate customer-identification and segmentation processes, and do so on a large scale. One implication is that AI-enabled systems can identify and address specific customers' contextual needs. This could result in better application and utilization of segmentation, which is a key marketing discipline (Smith, 1956; see also Ritter & Pedersen, 2024). Thus, AI offers plenty of opportunities to create value, making it vital for business-to-business firms to take note of this development.

Previously, the use of customer data and the application of customer analytics were predominantly powered by human intelligence. In other words, a human had to come up with a good question or a good business idea, and then find relevant data and analytics to answer that question or test the business model. The development of AI fundamentally changes this—machines can now ask and answer relatively complex questions. Millions of users are experimenting with AI-enabled systems, like ChatGPT, Copilot, Perplexity, and Gemini, and realizing that these systems are very good at asking interesting questions and providing interesting answers (Mollick, 2024). As mentioned above, the democratization of AI in combination with its perceived authenticity create many accounts of expected value creation. Yet, humans should remain in the loop both to secure validity and to co-create value with the machine (Mollick, 2024).

Regarding human actors, their entrepreneurial actions are important for translating the opportunities offered by digital authenticity into value creation (e.g., Alvarez & Barney, 2005). Regardless of whether entrepreneurial opportunities are formed based on discovery or creation theory (Alvarez & Barney, 2007), it demands human action to initiate transformational action. Therefore, entrepreneurial action is included in the theoretical framework (Fig. 1) to indicate the importance of humans for realizing value creation—in particular in digital transformation.

5. Research agenda

Ever since the publication of Turing's (1950) seminal work on the Turing test (or the "imitation game"), computer scientists have been

[15] Ibid.

fascinated with the idea of developing and testing the capacity of machines to exhibit intelligence to such an extent that their output is indistinguishable from that of humans. In the current phase of digitalization, advances are accelerating and the Turing test appears to have been passed—we can no longer pinpoint the originator of a document, the counterpart in an interaction, or the origin of a dataset as human or artificial—and we cannot be sure that an artefact, an interaction, or a dataset that seemingly relate to a person, a place, or a time in fact also is truthfully related and authorized. In other words, machines are as good (or as bad) as humans. Against this backdrop, we suggest the following research agenda for the fifth phase of digitalization (Table 6).

5.1. Research theme 1: The impact of digital authenticity

One overarching research topic is the impact of digital authenticity on business-to-business marketing. As this phase is new and evolving, little research has shed light on how business-to-business relationships or the practice of business-to-business marketing change owing to the existence of AI-enabled systems. For instance, a significant part of business-to-business marketing theory and practice builds on the notion of interpersonal relationships and how trust and commitment contribute to business-to-business relationship success. How does this change when parasocial interactions with an intelligent, yet artificial, agent enter the scene? There is a pressing need to update our established theories and axioms to reflect the new (artificial) reality and the challenges that unauthorized digital authenticity may create. Timewise, the changes are happening now. If we want to understand the transitions and developments, we need to study this phenomenon as it develops. Otherwise, researchers will be forced to report in hindsight—and business-to-business practice is left with experimentation.

Table 6
Research agenda.

RESEARCH THEME	TENTATIVE RESEARCH QUESTIONS
Theme 1: *The impact of digital authenticity on business-to-business marketing*	How will digital authenticity affect business-to-business marketing? How do interpersonal business relationships change when parasocial interactions with an intelligent, yet artificial, agent enter the scene?
Theme 2: *Authentication in business markets*	To what extent will actors in business-to-business markets miss the ability to determine a certain origin? How can such a need be fulfilled? What are the positive and negative impacts of digital authenticity and the lack of authentication?
Theme 3: *The impact of phase 5 on marketers' jobs*	Will business-to-business marketing employees be supported or displaced? How will business-market functions (i.e., tasks and units) evolve in the era of digital authenticity? Will entire functions be replaced by AI systems? If not, what role will marketing professionals play?
Theme 4: *The interaction processes of AI systems*	What rules and norms are likely to develop about the use of human-like AI in supplier-customer relationships? Will revelation of the true nature of the interaction be a requirement? How are different digital technologies assessed in terms of the uncanny valley hypothesis in business markets? What is the business impact of AI-enabled intimacy on interactions between businesses? Will AI lead to efficiency gains or relationship quality losses? How can machines improve intimacy? Can machines displace marketers' customer-intimacy capabilities?
Theme 5: *Synthetic data*	What methodological requirements should apply for synthetic datasets? What kinds of documentation and quality measures should be reported in academic research and in practice? How could synthetic data change business marketing in practice? How can discrepancies between synthetic and real data be managed?
Theme 6: *Unfortunate consequences of phase 5*	What are the positive and negative consequences of the fifth phase of digitalization? What are the intended and unintended consequences?

5.2. Research theme 2: Authentication in business markets

The increase in digital authenticity also demands new insights into authentication. More specifically, actor-specific verification of digital authenticity is required to avoid fraud and abuse. To what extent will actors in business-to-business markets miss the ability to ensure a certain origin? How can the need for authentication be fulfilled? We need to understand the positive and negative impacts of digital authenticity in combination with the lack of authentication. As mentioned earlier, we see this as two capabilities—one for developing, implementing, and utilizing AI-enabled systems for value creation, and one for developing, implementing, and utilizing authorization systems.

5.3. Research theme 3: The impact of phase 5 on marketers' jobs

Another pressing concern is the impact that phase 5 will have on business-to-business marketers' jobs. Will business-to-business marketing employees be supported or displaced by AI-enabled systems? Will the role of marketers accelerate in this phase or vanish? The claim of "the vanishing salesperson" (Wilson, 2000) is not new but maybe this time the threat is real. Business-to-business marketing professionals and machines may jointly contribute to creating an artefact, an interaction, or a database in the collaborative form of extended intelligence, but how this might materialize in practice is still an open question. In addition, certain marketing jobs (e.g., copywriters, market analysts, graphical assistants) may disappear or at least experience less demand. Against this backdrop, we see several questions as worthy of pursuit: How will business-to-business marketing functions (i.e., tasks and units) evolve in the era of digital authenticity? Will entire functions be replaced by AI-enabled systems? If not, what role will marketing professionals play in an AI-enabled future? Some early inroads into changes in the nature of organizational buying centers to include intelligent agents have already been made (e.g., Pedersen, 2023). Can the application of AI improve business-marketing practices, especially in situations where personal interaction is a main component of the business relationship? AI poses profound questions and challenges for the practice of business-to-business marketing but also offers great potential for value creation.

5.4. Research theme 4: The interaction processes of AI-enabled systems

Similarly, the involvement of AI-enabled systems in interaction processes is new. AI may not only ensure that suppliers know their customers extremely well, but it may also use those insights to persuade or even manipulate customers. While earlier phases of digitalization helped with customer handling, the current phase has accelerated this capacity, and combined it with the capacity to make accurate inferences and target specific customers, both firms and members of organizational buying centers. Against this backdrop, we identify several emerging research questions: What rules and norms are likely to develop about the use of human-like, AI-enabled systems in supplier-customer relationships? Will revelation of the true nature of the interaction be a requirement? How are different digital technologies assessed in terms of the uncanny valley hypothesis in business markets? What is the business impact of AI-enabled intimacy on interactions and relationships between businesses? Will AI lead to efficiency gains or relationship-quality losses? How can machines improve intimacy? Can machines displace marketers' customer-intimacy capabilities?

5.5. Research theme 5: Synthetic data

In addition to the promising features of synthetic data discussed above, the creation and use of synthetic customer data entail the risk of creating "wrong" datasets, which would distance marketers from customers. Moreover, the use of AI-enabled systems to create synthetic data may result in a black box in which no one can control how or why the system creates the data. Therefore, methodological guidance is needed to ensure trustworthy results that are useful for theory and practice. While some studies have examined digital intelligence in marketing (e.g., Ma & Sun, 2020), the extant research has predominantly emphasized analytical applications after "real" data has been collected. Hence, synthetic data is an overlooked topic in marketing research, and has few established guidelines despite the important advances being made in adjacent fields and in practice. Given this backdrop, we highlight the following research questions: What methodological requirements should apply for synthetic datasets? What kinds of documentation and quality measures should be reported in academic research and in practice? How could synthetic data change business-to-business marketing in practice? How can we manage discrepancies between synthetic and real data?

5.6. Research theme 6: Unfortunate consequences of phase 5

Finally, we see a strong need for research to identify, document, and analyze unfortunate consequences of digital authenticity. That is, it is arguably necessary to study and reflect upon the consequences of digital authenticity beyond intended value creation. Merton (1936) provided the seminal conceptual terminology for work on consequences of actions, including consequences that are not planned or imagined at the action's initiation. According to Merton (1936, p. 895), "unforeseen consequences should not be identified with consequences which are necessarily undesirable (from the standpoint of the actor)" and, consequently, "undesired effects are not always undesirable effects." As such, we can distinguish between desired and undesired as well as between desirable and undesirable consequences of this new phase of digitalization. Against this backdrop, we should investigate how to realize the full business potential of AI-enabled artefacts, AI-enabled interactions, and AI-enabled datasets in business-to-business marketing, and develop an understanding of what we might lose in the process owing to undesirable consequences.

6. Managerial implications

While a great deal of research is still needed on the impact of generative AI on business-to-business marketing, we can already highlight the contours of several important managerial implications of this new phase of digitalization. In particular, we suggest the emergence of an additional set of "four Ps" for marketing in the phase of digital authenticity (Fig. 2): *prompting, proving, partnering,* and *permission*. While these do not replace the conventional Ps of marketing (whether they consist of four, seven, or nine Ps), they do add novel dimensions to consider and new capacities to develop in the new phase of digitalization. In the following, we explicate them in further detail.

Prompting has become a core capability of marketers in this new phase. The quality of AI-enabled output depends on the quality of the prompts. Thus, "AI prompt engineering" has become a highly paid

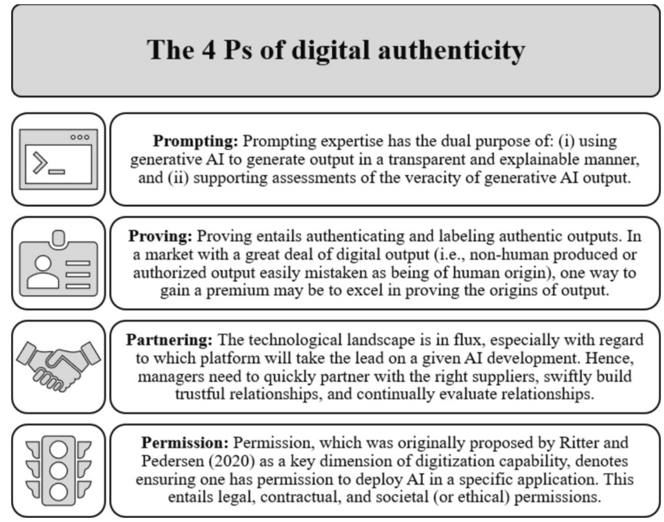

Fig. 2. The 4 Ps of digital authenticity in business-to-business marketing.

career path with annual salaries of up to USD 300.000.[16] Prompt writing is a skill needed to excel in the current phase (Mollick, 2024) and, therefore, industrial marketers must develop this capability and integrate it into existing processes. Being digitally authentic does not necessarily preclude prompting, but it requires that one is transparent about prompts and able to explain exactly how generative AI has been used (see the three criteria for digital authorization in section 3). A capacity for prompting also makes one more capable in verifying outputs (Hannigan et al., 2024) and more likely to correctly assess other AI-generated output in the market. Hence, prompting expertise has the dual purpose of: (i) using generative AI to generate output in a transparent and explainable manner, and (ii) supporting assessments of the veracity of generative AI output.

Proving entails authenticating and labeling authentic outputs. In a market with a great deal of digital-authentic output (i.e., non-human produced or authorized output easily mistaken as being of human origin), one way to gain a premium may be to excel in proving the origins of output. Therefore, industrial businesses need to demonstrate the authenticity and authorization of their outputs, which can arguably be seen as a new form of branding (i.e., "made by humans" (Broad, 2018), "humans in the loop" or "approved by humans"). As explained above, digital authenticity also entails full transparency about how generative AI has been included in the process, and about how it has been used (or not used). Hence, we see ample differentiation opportunities in terms of accurately labeling content and using the process to develop market-based credibility and trustworthiness.

Partnering denotes relationship building with the right partners in generative AI. While relationship building is crucial for business-to-business marketing in general, the technological landscape is in flux, especially with regard to which platform will take the lead on a given AI development. Hence, managers need to quickly partner with the right suppliers, swiftly build trustful relationships, and continually evaluate relationships. Thus, the whole spectrum of relationship management must be brought into play: acquiring, developing, maintaining, reducing, terminating, and blocking (Ritter & Geersbro, 2018). Therewith, core business-to-business marketing capabilities are key assets in developing the AI capabilities of business-to-business firms. Firms will need to apply their marketing capabilities including partner assessment, relationship development, and value co-creation towards their technology partners. Moreover, when the lines between artificial and

[16] https://www.forbes.com/sites/jackkelly/2024/03/06/the-hot-new-high-paying-career-is-an-ai-prompt-engineer/ accessed August 19, 2024.

authentic become blurred, it is also essential that established relationships remain trustful.

Permission, which was originally proposed by Ritter and Pedersen (2020) as a key dimension of digitization capability, denotes ensuring one has permission to deploy AI in a specific application. This entails legal, contractual, and societal (or ethical) permissions. In other words, do the law and the focal contracts allow for the use of AI in a certain manner? Is doing so acceptable from the broader societal and ethical perspectives? In particular, given the approval of the new AI Act in the EU, permission will be a crucial aspect. In the context of digital authenticity, the key questions will be: Will key stakeholders allow businesses to deploy generative AI in a specific manner? Do they assess it as authentic and authorized?

All of the four Ps enhance the digital authenticity of a business. Therefore, they comprise important managerial levers for developing a consistent marketing strategy in the fifth phase of digitalization, which is currently unfolding. Consideration of these new four Ps of marketing and the creation of capacities to support them will prove useful in the new phase of digitalization. However, these activities will also be challenging, as many firms are looking for similar types of talent and trying to build the same capabilities in their organizations.

7. Towards an authentic digital future

The pace and depth of digital-technology development can both excite and alarm. We are generally excited about the implications of this development for business-to-business marketing and we hope that our suggestion of the three dimensions of digital authenticity as an overall frame stimulates discussion. However, as we must also be cognizant of the very real dangers related to this new phase of digitalization, we have highlighted the need to discuss its consequences, in particular the need for digital authorization. In this regard, unintended negative consequences may be expected and those are of particular interest for research and practice.

Ritter and Pedersen's (2020) observations suggest that the various phases of digitalization each has a duration of about 10 years. If this trend is extrapolated to the fifth phase of digitalization, then it may be forecasted to be replaced around 2030. It will be interesting to see what phase 6 looks like. Some authors have already suggested that the next phase could involve human-like systems that have feelings, can engage in self-reflection and exhibit artificial general intelligence (Kaplan & Haenlein, 2019, Haenlein & Kaplan, 2021), or even surpass human intelligence in most domains (Bostrom, 2014). For now, there are still many pressing and unresolved questions we need to address in phase 5 before looking ahead.

CRediT authorship contribution statement

Carsten Lund Pedersen: Writing – review & editing, Writing – original draft, Conceptualization. **Thomas Ritter:** Writing – review & editing, Writing – original draft, Conceptualization.

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None.

Data availability

No data was used for the research described in the article.

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