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Research Article

HARNESSING TEXTUAL ANALYTICS FOR INNOVATION: A STUDY OF TOPIC MODELING APPLICATIONS

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Abstract

Innovation remains a central driver of economic growth, organizational competitiveness, and societal progress. In the digital era, the rapid expansion of unstructured textual data—ranging from customer feedback and social media content to scientific publications and patent documents—has created both opportunities and challenges for innovation management. Extracting meaningful insights from such vast and heterogeneous data sources has become a strategic necessity for organizations seeking to enhance decision-making across the innovation lifecycle. This study explores the role of topic modeling as a powerful analytical approach for uncovering latent thematic structures within large-scale text corpora.

Topic modeling, a class of probabilistic and unsupervised machine learning techniques, enables the systematic identification of hidden topics in textual data, offering a structured and interpretable means of transforming unstructured information into actionable knowledge. Unlike more recent large language models (LLMs), which are often general-purpose, computationally intensive, and prone to interpretability challenges, topic modeling provides a more transparent, reproducible, and domain-adaptable framework for text analysis. This makes it particularly suitable for innovation-driven contexts where clarity, consistency, and traceability of insights are essential.

Positioned within the broader field of natural language processing (NLP), topic modeling has gained renewed relevance due to advancements in big data analytics and computational linguistics. Its application spans various stages of the innovation process, including opportunity identification, trend analysis, knowledge management, and strategic foresight. By systematically organizing large volumes of textual data into coherent thematic clusters, topic modeling enhances the ability of organizations to detect emerging patterns, reduce informational complexity, and support evidence-based innovation strategies.

This paper highlights the theoretical foundations and practical applications of topic modeling in innovation management, emphasizing its value as a complementary tool to modern AI systems. It argues that despite the rise of large language models, topic modeling remains a critical methodology for structured knowledge discovery in text-rich environments. Ultimately, the study demonstrates that integrating topic modeling into innovation analytics frameworks can significantly improve the quality and reliability of insights derived from unstructured data.

Keywords: Topic Modeling; Innovation Management; Textual Analytics; Natural Language Processing; Unstructured Data

Introduction

Innovation has long been recognized as a cornerstone of economic growth, corporate competitiveness, and societal advancement. In the digital era, innovation management must contend with an unprecedented influx of unstructured data, ranging from customer reviews and social media content to academic publications and patent filings. These textual sources are replete with insights that, if properly extracted and analyzed, can inform decision-making across the innovation lifecycle. The ability to harness these insights has thus become a strategic imperative for modern organizations. One promising approach to this challenge is topic modeling—a family of probabilistic, unsupervised machine learning techniques that uncover latent thematic structures within text corpora.

Topic modeling is not a new invention, but its relevance has surged in recent years with the proliferation of natural language processing (NLP) tools and big data analytics. Positioned within the broader NLP landscape, topic models provide a mathematically interpretable and relatively transparent mechanism for organizing, summarizing, and deriving insights from large text datasets. While large language models (LLMs), such as BERT and GPT, have captured much of the recent attention in AI research, their general-purpose design, input limitations, and tendency toward hallucination pose limitations in domain-specific applications such as innovation management. In contrast, topic modeling offers a more controlled and customizable approach, with the capacity to generate reproducible and context-sensitive insights.

The core premise of topic modeling is the statistical inference of latent topics—unobserved thematic patterns that recur across documents. Techniques like Latent Dirichlet Allocation (LDA), Non-negative Matrix Factorization (NMF), Correlated Topic Models (CTM), and more recent neural models such as BERTopic, allow for scalable and interpretable analysis of unstructured text. These models assign distributions over topics for each document, and distributions over words for each topic, enabling analysts to summarize and visualize large bodies of text with remarkable efficiency.

Organizations are increasingly turning to topic modeling to power their innovation efforts. From ideation to commercialization, topic models help firms navigate dynamic consumer landscapes, track emerging trends, and evaluate internal R&D portfolios. For instance, Procter & Gamble has implemented real-time feedback systems using NLP and topic modeling to enhance product development cycles. DHL leverages voice-of-the-customer analysis to inform service innovation, while L'Oréal monitors social media and fashion blogs to anticipate beauty trends before they become mainstream. At a more strategic level, Siemens applies patent analytics via topic modeling to benchmark and guide innovation investments.

Beyond corporate use cases, topic modeling has also gained traction in academic innovation research. Governments and funding agencies use topic modeling to assess research trends, allocate resources, and evaluate scientific impact. The European Commission, for example, has employed topic modeling to monitor and forecast innovation trajectories in EU-funded projects. In parallel, journals like the *Journal of Product Innovation Management* (JPIM) serve as rich repositories of scholarly insight, and analyzing them with topic models can yield valuable meta-level understandings of the field's evolution.

Despite its growing adoption, the use of topic modeling in innovation management remains fragmented. Different models are often applied without sufficient consideration of their assumptions, suitability, or methodological rigor. This results in inconsistencies and hampers the comparability of findings across studies. Furthermore, while existing literature provides isolated examples of topic modeling applications in innovation, there is a lack of integrative frameworks that classify and evaluate these applications in relation to the stages of the innovation process.

To address this gap, this article makes several important contributions. First, we provide a comprehensive review of five dominant topic modeling approaches, highlighting their theoretical underpinnings, algorithmic characteristics, and practical implications. This review serves as a guide for researchers and practitioners navigating the complex landscape of topic modeling tools. Second, we propose a four-stage framework that maps topic modeling applications onto the core stages of innovation: idea generation, development, commercialization and evaluation, and academic research. This framework offers a structured lens through which to assess the relevance and effectiveness of different topic modeling strategies.

Third, we apply this framework in an empirical analysis of JPIM publications spanning four decades (1984–2023). Using topic modeling, we identify key research themes, track their evolution over time, and highlight underexplored areas that may warrant future investigation. This illustrative case not only demonstrates the practical utility of our framework but also provides a replicable methodology for similar analyses in other domains.

Finally, we conclude by outlining future research directions and practical considerations for effective topic modeling deployment. These include the integration of hybrid models, the use of dynamic topic modeling to capture temporal changes, and the development of domain-specific taxonomies to enhance interpretability.

In sum, this article positions topic modeling as a versatile and powerful tool for innovation management. By systematically categorizing its applications and aligning them with innovation processes, we aim to demystify the technique and empower innovation stakeholders to make informed, data-driven decisions. As organizations increasingly seek to extract value from unstructured data, topic modeling stands out not just as a technical solution, but as a strategic enabler of innovation.

DIGITAL TECHNOLOGIES

The emergence of numerous DTs—defined as the combination and connectivity of dispersed information, communication, and computing technologies (Bharadwaj et al., 2013; Hanelt et al., 2021)—has engendered new products, novel business models, and innovative processes (Ciarli et al., 2021; Hendrix, 2014; Nambisan et al., 2019). Because they also trigger company-wide organizational changes and transformational opportunities, these technologies are often called digital transformational technologies (Hanelt et al., 2021).

These new DTs fundamentally differ from prior, primarily information technologies (Verhoef et al., 2021). The earlier technologies focused mainly on converting analog information into digital information and required only incremental changes within firms (Hanelt et al., 2021). In contrast, the newer DTs encompass a wide array of technologies; also, they alter a firm's entire way of doing business (Verhoef et al., 2021) because they require a transition from an information technology (IT) based strategy to a DT-based strategy to create and appropriate value (Bharadwaj et al., 2013).

Given the extensive array of enabling DTs, extant research has typically organized them into a variety of parsimonious categories based on the research purpose and focus. For example, Appio et al. (2021) classified DTs into AI, big data, IoT, and smart products. Hoyer et al. (2020) and Flaherty et al. (2021) grouped DTs into the Internet, mobile platforms, and social media channels. Rindfleisch et al. (2020) classified DTs into 3D printing, augmented reality, AI, big data, blockchain, robotics, and social media, while Ciarli et al. (2021) organized DTs into AI, big data, blockchain, cloud computing, and IoT. Our synthesis of prior research shows that the following seven categories effectively capture the wide breadth of DTs: artificial intelligence (AI), extended reality (XR), social/interactive technologies, mobile technologies, the Internet of Things (IoT), sensory technologies, and blockchain technologies. Each of these seven categories is briefly explained next.

Artificial intelligence

AI reflects a “system's ability to interpret external data correctly, learn from such data, and use those learnings to achieve specific goals and tasks through flexible adaptation” (Haenlein & Kaplan, 2019, p. 17). Shankar (2018) states that AI refers to programs, algorithms, and machines demonstrating intelligence; similarly, Syam and Sharma (2018) define AI as devices that mimic “intelligent” human behavior. Davenport et al. (2020) and Huang and Rust (2021) note that AI underpins several technologies, ranging from machine learning and deep learning algorithms to chatbots, drones, and robots.

Huang and Rust (2021) posit that marketers can leverage three distinct types of AI: mechanical, thinking, and feeling. Mechanical AI refers to technologies such as clustering algorithms designed to automate repetitive and routine tasks. Thinking AI processes data to arrive at new conclusions; text mining and speech and facial recognition technologies illustrate thinking AI technologies.

Feeling AI is intended for two-way interactions with humans and analyzing human feelings and emotions. Text-to-speech technology, chatbots that mimic human speech, and robots that can sense affective signals are examples of feeling AI technologies. The recently popular generative AI technologies (e.g., Bard and ChatGPT) have further accelerated these changes. These multiple types of AI facilitate innovation across a broad spectrum of marketing activities.

2.2 | Extended reality

Extended reality (XR) refers to digitally enhanced environments and encompasses augmented reality (AR) and virtual reality (VR) environments. While AR refers to experiences in which the real world is enhanced with digital objects, VR denotes complete immersion in a digital environment. Xi and Hamari (2021) expect the XR market to grow exponentially from US $3.13 billion in 2017. This growth will stem from using XR to build stronger customer relationships through enhanced customer experiences and greater customer co-creation opportunities (Meißner et al., 2020). The early VR technologies were non-immersive; standard-sized computer screens or monitors were used to present the virtual environment, and users could only interact with them with computer keyboards or mice (Suh & Prophet, 2018). Recent developments such as VR headsets and Cave Automatic Virtual Environments have been motivated by the goal of designing fully immersive environments that closely mimic the physical properties of the real world in real-time (Blascovich et al., 2002). Xi and Hamari (2021) note that stereoscopic head-mounted display devices on which a different visual feed is transmitted to each eye to create a three-dimensional (3D) experience are a defining aspect of the latest VR technologies. With a VR interactive device, users can navigate 3D artificial worlds as if they were in this imaginary environment (Suh & Prophet, 2018). Similarly, newer multi-sensory AR technologies can enhance customers' experiences by providing simulated physical control with environmental embedding (Hilken et al., 2017).

Social/interactive technologies

Consumers spend more time on social media sites like Facebook and LinkedIn (Moe & Schweidel, 2017). Consequently, firms have embraced social media to engage and interact with customers (Kumar et al., 2016). Moe and Schweidel (2017) note that organizations regard social media as another channel through which to disseminate brand messaging to customers. A unique aspect of social media is that it allows two-way communication between firms and customers and peer-to-peer communication through a digitized social network. Social media empowers customers because instead of being solely passive recipients in the marketing exchange process, they can voice their opinions and contribute to changes in products and strategies (Roberts & Candi, 2014). As such, firms monitor social media sites as a source of marketing research, collecting and analyzing data, and crowdsourcing new product ideas.

Mobile technologies

Mobile technologies have reshaped how marketers interact with customers (Tong et al., 2020). The proliferation of portable computing devices (e.g., smartphones and wearable devices) and mobile services (e.g., apps and virtual assistants) has created innovative marketing opportunities. Specifically, mobile technologies allow marketers to collect data on consumers' behavioral and environmental contexts to develop adaptive and personalized promotion and pricing strategies (Zubcsek et al., 2017). Using mobile technologies to create innovation-based differentiation has considerable potential, as 97% of U.S. consumers own a mobile phone (Pew Research Center, 2021). Furthermore, adults spend over four hours daily consuming digital media on their mobile devices (eMarketer, 2021). Mobile promotions have become increasingly important with the widespread use of mobile devices (Andrews et al., 2016).

Internet of things

The Internet of Things (IoT) denotes physical objects interconnected via the Internet (Ashton, 2009). Embedded with sensors and communication software, such connected devices permit remote identification, sensing and communication, and data collection (Ashton, 2009). IoT helps improve the management and productivity of equipment and devices connected to the Internet. Raff et al. (2020) argue that IoT devices' identification and communication aspects provide significant value. For example, a connected product can provide continuous access to data regarding modes of application and component wear and tear (Saarikko et al., 2017). This information, in turn, can help refine existing products and guide future new product development (NPD) based on data rather than guesswork (Suppatvech et al., 2019). From a marketing perspective, customer service activities such as maintenance contracts help provide added value.

Connected products enable firms to provide services at needed intervals, ensuring optimal efficiency (Saarikko et al., 2017).

Sensory technologies

Sensory technologies are devices that detect and respond to changes in the environment. They are equipped with sensors and actuators to sense signals in their surroundings (Raff et al., 2020). Examples of products that incorporate such technologies include car lane assistant systems and car braking assistants. These products are enabled by complex software that allows them to operate according to a sensing and responding logic (e.g., activation of a car's brakes when sensing an obstacle ahead) (Raff et al., 2020). Other sensory technologies include eye-tracking technologies, which can be used to determine the side of a grocery store aisle that customers pay more attention to and the shelf level that is most likely to attract shoppers' attention (Chen et al., 2021).

Blockchain

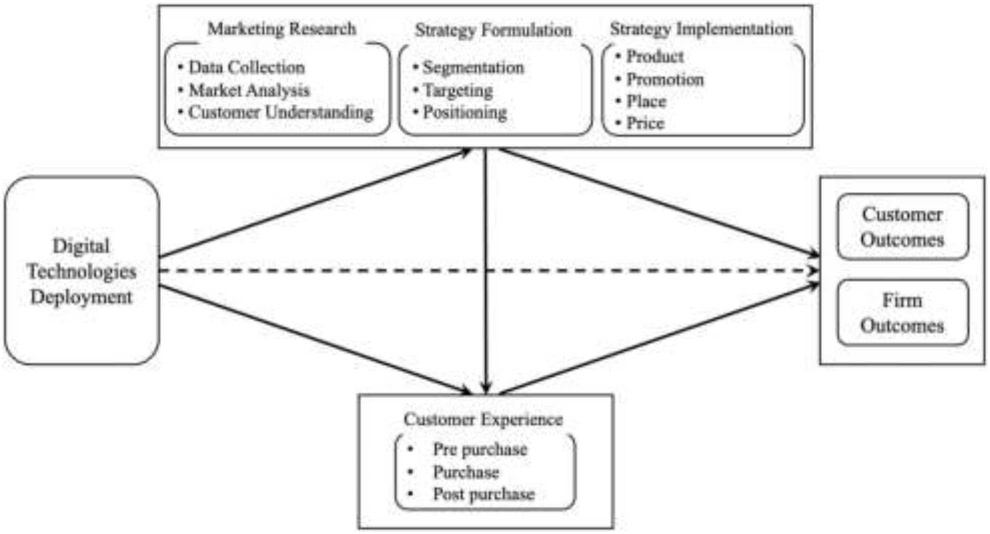
Blockchain, or a “peer-to-peer network that sits on top of the internet” (Iansiti & Lakhani, 2017), is also relevant for marketing innovations (Gleim & Stevens, 2021). It comprises a decentralized, transparent, and immutable database of digital events. These attributes make it attractive for marketing activities like market research and online advertising (Gleim & Stevens, 2021). For example, online market research sites like MTurk have led to concerns regarding data quality. Blockchain can raise confidence in online data collected through smart contracts that ensure agreed-upon conditions are met (e.g., time spent per question) before paying respondents using cryptocurrency. Similarly, blockchain can mitigate concerns about using chatbots to increase click rates by ensuring that consumers have authenticated profiles.

Specific technologies considered

We believe that all the technologies discussed above have a role in marketing innovations – albeit in different marketing activities. Therefore, we include all of them in our literature search and assess their impact on marketing activities. Given our interest in being comprehensive and not excluding any specific technologies, we used the classifications noted in prior literature as a starting point to identify a comprehensive list of DTs for our literature review. This ensures we include all relevant technologies without being constrained by specific classifications.

METHODOLOGY

We followed the literature search process commonly adopted in top business journals (e.g., Denyer & Tranfield, 2009; Micheli et al., 2019). We considered only peer-reviewed journals because they disseminate validated knowledge and have the highest impact (Crossan & Apaydin, 2010). We used the Web of Science Social Sciences Citation Index and the Science Citation Index Extended databases, which provide comprehensive sources of peer-reviewed journals relevant to our study (West & Bogers, 2014). As shown in Web Appendix 1, we identified relevant articles using two subsets of Boolean search terms. To cast a wider net, we used truncated words in our search. The first subset included digit* or innovat* or market* or tech* or customer experience*. The second subset encompassed a comprehensive list of technologies that have been noted as relevant in recent articles on DT and innovation (see, for example, Appio et al., 2021; Bresciani et al., 2021; Ciarli et al., 2021; Verhoef et al., 2021). Thus, this second subset included 3d print* or 4.0 machines or 5G or additive manufacturing or algorithm or artificial intelligence or augmented reality or big data or blockchain or cloud or crypto* or deep learning or digital control systems or digital payment or digital platform* or digital technolog* or digital twin* or drone* or extended reality or geo or information and communication technolog* or interactive media or Internet of things or machine learning or metaverse or mobile or online payment system or robot* or sensory or smartphone* or smart product* or social media or speech recogn* or virtual mirror or virtual reality or world wide web. We conducted a topic search (title, keywords, or abstract) using these Boolean search terms (including both subsets at once). Our review included articles published since 2000 to ensure a more comprehensive search. This search process generated 688,216 articles published between January 1, 2000, and December 31, 2022.
Given our focus on the link between DT and marketing innovations, we further narrowed the search to the following Web of Science categories: “business,” “management,” and “operations research management science.” We limited the search to “articles,” “review articles,” and “early access articles,” which resulted in 31,648 relevant articles. Then, to ensure a base level of quality, we only included articles published in journals



classified in the top two quartiles in Journal Citation Reports (JCR). This process resulted in 3343 articles. Organizing framework.

authors independently reviewed the abstracts of all these articles to determine whether they were related to the study's focus on marketing innovations. As a result of these efforts, we identified 245 articles as relevant for additional detailed analysis. After reading each of these 245 articles, 194 articles that incorporated empirical evidence relating DTs to marketing innovations were identified. A third author read these 194 articles and confirmed the selection.

ORGANIZING FRAMEWORK

Figure 1 shows our organizing framework. It depicts the role of DTs in marketing innovations that enhance the customer experience and elevate organizational outcomes. To provide appropriate contextual clarity regarding the focus of our systematic review, we next elaborate on strategic marketing planning and customer experience as core components of the framework.

Strategic marketing planning

Huang and Rust (2021) state that strategic marketing planning is a process that begins with marketing research followed by marketing strategy formulation (segmentation, targeting, and positioning) and marketing strategy implementation (product, promotion, place, and price). Following their prescription, we focus on innovations related to this process that DTs enable. Because such innovations permit differentiation opportunities via elevated customer experiences, we elaborate on this component next.

Customer experience

While the relevance of customer experience was first recognized over 50 years ago (e.g., Dewey, 1963), companies began focusing on customer experience as a source of competitive advantage relatively recently (Bustamante & Rubio, 2017). To illustrate, Jeff Bezos of Amazon stated: “If there's one reason we have done better than our peers…, it is because we have focused like a laser on customer experience…” (Bezos, 2016). Not surprisingly, customer experience management has received increased attention as an important source of competitive advantage (Homburg et al., 2017). Stephens (2013) argues that “average” customer experiences are no longer good enough. Keiningham et al. (2020, p. 432) concur and note that “… demands for real-time and adaptive experiences are part of the new business reality.”

These heightened customer expectations are motivated, in large part, by DT-enabled marketing innovations that facilitate customized customer journeys (Hoyer et al., 2020). For example, virtual agents can answer customer questions, provide recommendations, and deliver advice to motivate purchase (Parise et al., 2016), while smart mirrors can display complementary items to complete fashion outfits (Huang & Rust, 2021). Hoyer et al. (2020) state that DTs can redefine the customer journey by creating and transforming new touchpoints. To better understand how, we adopt Lemon and Verhoef's (2016) conceptualization of customer experience as a journey that entails touchpoints from prepurchase to purchase and postpurchase. Prepurchase includes the entire experience before purchase: needs recognition, search, and purchase consideration behaviors. Purchase covers all interactions with the firm during the purchase event and incorporates choice, ordering, and payment behaviors. Postpurchase encompasses customer interactions following purchase and includes behaviors such as usage/consumption and service requests.

FINDINGS

Descriptive analysis

Our systematic review confirms the growing research attention paid to DTs as an impetus and source for marketing innovations; we also provide a comprehensive view of the role of DTs in marketing innovations. As Web Appendix 1 indicates, between 2000 and 2010, only nine articles investigated the topic; in contrast, from 2011 to 2022, there were 185 published studies on the topic. Of note is the spike in publications (48 articles) in 2021; this spurt was likely a consequence of journals acknowledging the importance of the topic by devoting special issues to it (Appio et al., 2021). For example, the Journal of Business Research and the Journal of Product Innovation Management (JPIM) had special issues focusing on DTs and innovation. Besides these journals, research on DTs and marketing innovations has been published in various business-related journals (see Web Appendix 3).

A synthesis of this research (Web Appendix 4) shows that the relevance of mobile and social media technologies for marketing innovations has received the greatest research attention to date. Fifty-four articles have examined the link between mobile technologies and marketing innovation, while 51 studies have investigated the impact of social media-related marketing innovations. Further, while machine learning (25 articles), VR (19 articles), AR (19 studies), AI (17 studies), and geolocation (12 studies) have received some research emphasis, several recent technologies, such as blockchain, the metaverse, and drones, have received little to no research attention.

Web Appendix 4 also reveals that research relating DTs to marketing innovations has been conducted primarily in the United States (53 studies) and China (24 studies); in contrast, only seven studies have been done in India. Further, as seen in Web Appendix 5, the research context primarily comprises B2C settings (173 studies); in contrast, B2B has received relatively little attention (14 studies). Finally, Web Appendix 6 provides an overview of various data collection methodologies used in extant research. It shows that 69 articles relied on secondary data; when primary data was collected, the typical data collection approaches used were experiments (64 articles) and surveys (41 articles).

We also point out that although the generative AI technologies were available for use in the technology domain, the November 2022 introduction of ChatGPT for general public use has significantly altered the DTs landscape in marketing. Given that this is an emerging field, no academic research has formally investigated the role of ChatGPT in marketing. Still, we anticipate that marketing scholars and practitioners will become increasingly mindful of, optimistic about, and concerned about generative AI technology.

Integrative analysis

The above descriptive analysis regarding the technologies studied and the research context for these studies are valuable starting points for reviewing the state of research on the interface of DTs and marketing. We enrich these findings by synthesizing the 194 studies using the two organizing frameworks noted earlier, i.e., strategic marketing planning and customer experience. We integrate these firm (i.e., strategic marketing planning) and customer (i.e., customer experience) perspectives to critically evaluate the overarching themes in existing studies and identify gaps, which in turn provide useful directions for future research. In other words, using these two frameworks as a sieve permits a more nuanced lens to examine the role of DTs in marketing innovations for enhanced customer experiences.

To recap, we follow Huang and Rust (2021) and regard strategic marketing planning as a process that incorporates conducting market research, strategy formulation, and strategy implementation. Conducting market research comprises data collection, market analysis, and customer understanding. Data collection refers to gathering information about customers and competition, while market analysis denotes insights related to competitive advantages and market trends. In contrast, customer understanding encompasses customer needs, wants, feelings, attitudes, and preferences. Strategy formulation incorporates segmentation, targeting, and positioning, while strategy implementation involves organizational actions related to product, promotion, place, and price.

Also, as noted previously, we adopt Lemon and Verhoef's (2016) conceptualization of customer experience as a journey that entails touchpoints during prepurchase, purchase, and postpurchase. Prepurchase includes need recognition, search, and purchase consideration behaviors. Purchase covers all interactions with the firm during the purchase event and encompasses behaviors such as choice, ordering, and payment. At the same time, postpurchase refers to customer interactions following purchase and includes usage, consumption, engagement behaviors, and service requests.

Table 1 summarizes the number of articles that study DT-enabled marketing innovations at various customer journey stages; a more detailed synthesis follows. In this synthesis, we identify some themes and provide exemplars. Given the large number of articles, it is impossible to describe findings from each article in the text of our article, but a summary appears in Web Appendix

5.2.1 | DTs at the marketing researchcustomer journey interface

As seen from Web Appendix 4, considerable research (43 articles) has investigated the role of DTs in marketing research-related innovations throughout the customer journey. This is not surprising because social media, online reviews, and search platforms provide marketers with large amounts of textual data that can be harnessed with emerging technologies such as AI and machine learning. Several studies have highlighted the role of online searches by consumers as important sources of data collection during the prepurchase stage of the customer journey. Illustratively, Zhang et al. (2023) demonstrate that machine learning can extract consumer opinions from massive online text reviews, which, in turn, can help identify nuanced areas for product and service improvement. Kumar et al. (2021) note the use of artificial intelligence by companies like Amazon to collect data during purchases to generate recommendations for future purchases. Further, Vermeer et al. (2019) illustrated how firms can use machine learning to identify postpurchase electronic word-of-mouth communications (e.g., on Facebook and Twitter) that require a response to maintain brand reputation.

Concerning market analysis, Liu et al. (2016) illustrate how machine learning algorithms can analyze Twitter tweets during the prepurchase and purchase phases to improve market forecasting accuracy. In the postpurchase stage, information shared on social media can be used to identify emerging market trends proactively (Nguyen et al., 2015). Finally, studies have also highlighted how DTs can facilitate innovations related to customer understanding. During prepurchase, machine learning approaches can identify customer needs based on user-generated content (UGC) from online product reviews, blogs, and social media posts (Timoshenko & Hauser, 2019). Similarly, Du et al. (2015) show that trends in online searches for product features (e.g., the use of Google Trends) can alert marketers to product feature preferences during purchase. Finally, Hartmann et al. (2021) demonstrate how machine learning algorithms can help marketers analyze post-purchase social media posts (e.g., brand selfies) to evaluate and promote brand engagement.

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DTs at the marketing strategy formulation-customer journey interface

As with the role of DTs in marketing research innovations, the relevance of DTs to innovations in marketing strategy formulation has also received considerable research attention (39 articles). A close examination of Web Appendix 4 shows that segmentation, targeting, and positioning studies have focused on AI, mobile, and social media technologies. Also, in comparison with studies on segmentation (six studies) and positioning (eight studies), extant research has primarily emphasized the targeting aspect of strategy formulation (30 studies). As a case in point, Trusov et al. (2016) show how machine language and natural language processing can uncover target markets from customers' online surfing data. Similarly, Sun et al. (2022) demonstrate how a deep-learning algorithm can analyze customers' omnichannel prepurchase behaviors (i.e., online browsing and offline travel) to target customers more likely to purchase.

Further, the rapid increase in the use of mobile devices has prompted several studies on how mobile technologies can be used to track and target customers during the purchase phase (see, for example, Fang et al., 2015; Park et al., 2018). These mobile devices permit more effective targeting strategies such as geofencing (i.e., targeting customers near a firm's location) and geoconquesting (i.e., targeting customers near a competitor's location) (Bernritter et al., 2021; Fang et al., 2015). Hui et al. (2013) found that using mobile promotions to target shoppers while they are in a store motivates unplanned purchases. Finally, Salminen et al. (2022) show that machine learning can analyze customers' postpurchase tweets about “pain points” to target them with potential solutions.

Compared with emphasizing how DTs can facilitate innovative targeting approaches during prepurchase, few studies have focused on using DTs for segmentation and positioning during the customer purchase journey. Timoshenko and Hauser (2019) showed how machine learning could be used to analyze UGC during prepurchase to segment the market and develop strategic positioning strategies. Similarly, Padilla and Ascarza (2021) developed a machine-learning model that analyzes customers' purchase behaviors to segment them into high- and lowvalue (i.e., those unlikely to make a future purchase) customers. Further, the earlier referenced study by Salminen et al. (2022) used customer-tweeted pain points after purchase as the basis for market segmentation before targeting efforts. Finally, besides Timoshenko and

Hauser's (2019) study that illustrated the use of machine learning for positioning during prepurchase, Godey et al. (2016) found that social media communications during purchase have a positive effect on desired brand positioning; such activities also facilitate brand engagement postpurchase.

DTs at the strategy implementation [product]-customer journey interface

Following Huang and Rust (2021), we conceptualize products broadly as offerings (goods or services) that meet customer needs and wants regarding design, packaging, branding, returns, and associated customer service activities. Web Appendix 4 shows that 35 articles have studied the relevance of DTs for product/service-related innovations. During prepurchase, new product ideas can be generated using machine learning algorithms on user-generated content (UGC) from product reviews, blogs, and social media posts (Timoshenko & Hauser, 2019). A similar approach can also help identify "lead-user" innovations (von Hippel & Kaulartz, 2021). Research has also noted the relevance of voice assistants (VA) and chatbots during prepurchase. McLean et al. (2021) found that a VA's perceived intelligence and social attraction can motivate purchase decisions.

Regarding chatbots, Kushwaha et al. (2021) showed that interactions with a chatbot can lead to higher purchase intentions when brands are trusted, while Crolic et al. (2022) found that chatbot anthropomorphism harms purchase intention when customers enter the chatbot conversation in an angry emotional state. The relevance of DTs during purchase is best illustrated by innovations such as bots that can make purchases on behalf of humans via secure bot-to-bot transactions (Kumar et al., 2021). In addition, Mariani and Wamba (2020) found that big data analytics and machine learning can help forecast the likelihood of product innovations being purchased. Concerning the postpurchase phase, AI's relevance for customer service activities has received increasing attention. In particular, scholars have noted the growing use of chatbots to handle massive customer queries postpurchase (Huang & Rust, 2021; Luo, Tong, et al., 2019). A separate stream of research has studied the role of "smart products" in fostering customer engagement postpurchase. For example, communication technologies allow smart vacuum cleaners to convey preventive maintenance requirements and avoid potential breakdown costs (Raff et al., 2020). Empirical studies show that customers' satisfaction with chatbots during the postpurchase stage is contingent on their perception of receiving quality communications (Chung et al., 2020). Also, customers' postpurchase social media posts provide helpful guidance for subsequent product modifications (Salminen et al., 2022).

DTs at the strategy implementation [promotion]-customer journey interface

Web Appendix 4 shows that the role of DTs in promotion-related innovations has received the greatest research attention (117 articles). In particular, extant literature highlights the relevance of social media, machine learning, and mobile geolocation technologies for promotion-related innovations. Firms can post on social media during prepurchase to communicate current and future product offerings and promotions (Agnihotri et al., 2016). Zhang et al. (2021) found that such posts can alleviate customer uncertainty and promote new product adoption. Similarly, Godey et al. (2016) found that social media marketing positively influences consumers' preferences for luxury brands. Machine learning is also gaining importance in prepurchase promotion innovations. Swaminathan et al. (2022) show how machine learning can be used to analyze Twitter data to understand a brand's positioning as a starting point for developing appropriate marketing communications. Similarly, Trusov et al. (2016) demonstrated how machine learning-based modeling can uncover individual user profiles from online surfing data so firms can tailor their promotional offers accordingly. Finally, because mobile technologies enable marketers to leverage locational and temporal information about customers, these technologies enable novel mobile promotional campaigns like customized advertising (Ketelaar et al., 2018).

During the purchase phase, mobile technologies enable marketers to offer location-based promotions (e.g., mobile coupons), which can be personalized based on geofencing or geo-conquesting (Fang et al., 2015; Fong et al., 2015). For example, locationbased technologies enable retailers to be notified when customers are in their stores so they can push promotions to them (Bernritter et al., 2021). Kumar et al. (2016) found that firm-generated content (FGC) on social media positively impacts customer spending. Further, Humphrey et al. (2017) found that even incidental exposure to a firm's social media posts increases brand choice. Postpurchase social media posts that elicit customer responses, such as "likes" or comments, facilitate brand engagement (Kumar et al., 2016; Unnava & Aravindakshan, 2021). Also, in B2B settings, the salesforce can use social media communications to increase customer satisfaction
(Agnihotri et al., 2016).

DTs at the strategy implementation [place]-customer journey interface

The role of DTs in place-related innovations has received considerable attention in extant literature. Web Appendix 4 indicates that 55 articles have focused on the topic; they have investigated the relevance and import of a wide range of technologies ranging from older technologies like the Internet and the World Wide Web to newer technologies like AI and VR (six articles). Concerning the prepurchase phase, the relevance of new mobile and online-related technologies has received extensive attention. Mobile apps (Park et al., 2018; Park et al., 2020; Wang et al., 2015) and digital payment technologies (Adhikary et al., 2021) have propelled the growth of mobile channels. Similarly, AR and VR have driven the growth of online retail. According to Tan et al. (2022) , these technologies make it possible to substitute direct product experiences with virtual experiences that facilitate product evaluation and reduce product fit uncertainty. 3D VR (Kang et al., 2020), virtual fitting rooms (VFRs) (Yang & Xiong, 2019), and virtual mirrors
(i.e., interactive image technologies that allow consumers to construct personalized virtual models to try on products in a virtual setting; Cho & Schwarz, 2012) are among the technologies that can enrich customers' experiences in online channels before purchase. In addition, social AR (i.e., technology that allows customers to exchange product recommendations; Hilken et al., 2020) and sensory-enabling technologies (e.g., haptics) (Luangrath et al., 2022) can enhance customers' prepurchase experiences in online environments.

DTs also enable place-related innovations during purchase. For example, Kumar et al. (2021) note the role of machine vision, IoT sensors, and mobile app technologies in facilitating quicker purchase processes at retail stores (e.g., Amazon Go). Meißner et al. (2020) studied consumers' purchasing behaviors in highimmersive VR environments and found that these environments increase consumers' variety-seeking while lowering their price sensitivity. Similarly, Tan et al. (2022) found that AR usage on a retailer's mobile app can increase sales, particularly for less popular brands, products with narrower appeal, and more expensive products. Luo, Tong, et al. (2019) investigated the use of AI chatbots during purchases and found that undisclosed chatbots were as effective as proficient salespeople in motivating customer purchases. However, disclosing chatbot identity reduced purchase rates by almost 80 %.

Compared with the prepurchase and purchase phases of the customer journey, research on DT-enabled place innovations postpurchase is scarce. However, Yang and Xiong (2019) found that postpurchase customer satisfaction is higher when virtual fitting rooms (VFR) are available than when they are not; further, VFR also lowers the rate of product returns. Both effects are greater for personalized VFR than non-personalized VFR. Finally, Chang and Kim (2022) studied the use of service robots on customer satisfaction. They found that because service robots are regarded as social entities, perceptions of robot warmth and competence can enhance customer satisfaction.

DTs at the strategy implementation [price]-customer journey interface

Price includes payment tasks, price setting, and price negotiations (Huang & Rust, 2021). Although scholars (see, for example, Gleim & Stevens, 2021; Huang & Rust, 2021) have noted the relevance of emerging technologies for pricing innovations (e.g., the use of AI for dynamic pricing and cryptocurrency for payment), DTenabled pricing innovations have received little attention to date (eight studies per Web Appendix 4). Also, this research has been conducted primarily in online settings, focusing on the relevance of machine learning, mobile payment, and social media technologies. Concerning the prepurchase phase, Luo, Lu, and Li (2019) showed that cart tracking technologies can be used to offer price incentives to online shoppers who had paused their purchase journey (i.e., had left items in their purchase carts) to motivate the resumption of their purchase journeys. Similarly, Lee et al. (2016) found that positive social media reviews can help offset the quality concerns associated with lower-priced products and stimulate purchases in online shopping environments. Finally, Ferreira et al. (2016) demonstrated the use of a machine learning algorithm on an online retailer's sales transaction data to predict demand as a starting point to optimize pricing decisions.

Regarding pricing innovations during the purchase stage, Falk et al. (2016) found that mobile payments have a greater positive impact on purchasing behavior than cash or credit card payments. Similarly, Dube et al. (2017) showed that offering customer pricing discounts in real-time (using mobile technologies-based geolocation) increases the likelihood of purchase. Concerning postpurchase, Kumar et al. (2021) note that artificial intelligence-based bots can motivate ongoing brand engagement by automatically monitoring and comparing prices to recommend repurchases. Similarly, Godey et al. (2016) note that social media marketing can enhance brand loyalty for high-priced (e.g., luxury) products.

Digital technologies and outcomes

Web Appendix 4 shows that besides studying how DTs enable marketing innovations that facilitate customer experience management, extant literature has also investigated the impact of DT-enabled innovations on customer and firm outcomes. A total of 137 studies examined customer outcomes; of these, 20 also investigated firm outcomes.

Customer outcomes

The customer outcomes studied included customer satisfaction, purchase intention, and purchase behaviors. For example, Yim and Yoo (2020) found that digital menus increase customers' enjoyment of less-experienced foods, leading to higher intent to adopt and more ordered dishes. Because using digital assistants (e.g., chatbots) can enhance customer service (Hoyer et al., 2020) , researchers have tried to understand how to increase chatbot effectiveness. Longoni and Cian (2022) showed that customers believe that AI-based recommenders are more competent when assessing utilitarian attribute value and generating utilitarian-focused recommendations; however, human recommenders are perceived to be more competent when assessing hedonic attribute value and generating hedonic-focused recommendations. Luo et al. (2019) found that undisclosed chatbots are more effective in obtaining customer purchases than inexperienced workers; however, disclosing a chatbot's identity before making the sale significantly reduces purchase rates. Crolic et al. (2022) showed that when customers enter a chatbot-led service interaction in a nonangry emotional state, chatbot anthropomorphism positively affects customer satisfaction and subsequent purchase intention; however, this is not the case for angry customers.

Gelbrich et al. (2021) found that customer satisfaction increased when digital assistants provided emotional support (i.e., empathetic, reassuring expressions to customers who completed a task). In addition, Srinivasan and Sarial-Abi (2021) discovered that consumers respond less negatively to errors caused by an algorithm than a human. Concerning online ads, Ghose and Todri-Adamopoulos (2016) found that exposure to online ads increases customers' propensity to purchase; using this promotional technology is effective because, despite privacy concerns, few customers opt out of online. Bernritter et al. (2021) investigated the impact of location-based promotion strategies on customers' purchasing behavior. They found that combining geolocation targeting with the appropriate type of promotion can increase customers' purchase probability. Specifically, for low (product category) involvement consumers, in-store mobile ads led to a higher likelihood of buying a product than out-store mobile ads. Also, out-store mobile price promotions led to a higher purchase probability than non-price mobile promotions.

In terms of social media, Kumar et al. (2016) examined the effect of firm-generated social media content on customer spending (in total dollars) and cross-buying behavior (i.e., other product categories purchased by the customer). They found that messages posted by firms on their official social media pages have a positive, significant effect on customer spending and cross-buying. Studies have also investigated how the retail sector can generate favorable customer outcomes because it is rapidly evolving to incorporate virtual environments. Cho and Schwarz (2012) showed that consumers like the same product more when it is applied to their own smiling (vs. neutral) facial image in a “virtual mirror.” Yang and Xiong (2019) found that virtual fitting rooms (VFRs) can enhance postpurchase customer satisfaction; furthermore, personalized VFRs (i.e., the use of avatars based on a customer's face and body figure) increase customer satisfaction more than non-personalized VFRs. Kang et al. (2020) explore how 3D VR affects online purchasing decision-making and discover that because 3D enhances the playfulness and informativeness of the shopping interface, it positively influences product evaluation and purchase intention. More specifically, a playful interface enhances consumers' preference for hedonic product benefits (e.g., a stylish design), whereas informativeness is more important for subsequent purchase intention. Hilken et al. (2020) noted customers' increasing use of social AR (i.e., technology that enables them to communicate by sharing and virtually enhancing a common view of the physical environment). They found that when customers use such apps to help with decision-making, image-enhanced (vs. text-only) AR has a stronger impact on product choice.

Finally, Petit et al. (2019) called for further research on how sensory-enabling technologies can enhance the customer experience in online shopping environments. They posit that including sensory information in such environments is important because it can increase customers' confidence in their choices and enhance the likelihood of product purchase. In response, Luangrath et al. (2022) found that “vicarious touch” (i.e., observing a hand in physical contact with a product in a digital environment) positively affects consumers' psychological ownership and product valuation. In other words, a felt sense of body ownership communicated via the virtual hand has a “vicarious haptic effect.”

Firm outcomes

Besides the above studies on customer outcomes, 77 studies focused on firm outcomes (as noted above, 20 also investigated customer outcomes). These studies focused primarily on firm sales and revenues. Mullins and Agnihotri (2022) showed that the sales force's use of DTs (e.g., communication technologies) increases sales. Similarly, Chen et al. (2015) found that social media messages with a personal touch positively affect sales. Fang et al. (2015) showed that geolocation-based sales promotions boost impulsive (same-day) as well as delayed purchases. In addition, marketers can use “competitive locational” promotional targeting (i.e., geo-conquesting) to generate incremental sales without cannibalizing profits (Fong et al., 2015).

Tan et al. (2022) showed that using AR in retail settings positively affects sales. They attribute this effect to AR's facilitation of product evaluations before purchase by enabling customers to experience products virtually. Similarly, Yang and Xiong (2019) found that online retailers' use of VFRs can increase sales. However, personalized VFRs are counterproductive when combined with conventional product visualization(e.g., promotional photos featuring fashion models) because they elevate a customer's self-discrepancy. In addition to AR/VR, adopting IoT technologies increases online retail sales (Adamopoulos et al., 2021). This effect can be attributed to the increased convenience afforded by such technologies, which essentially automate customers' purchases. Furthermore, Adhikary et al. (2021) found that retailers that adopt digital payment technologies can increase their revenues.

FUTURE RESEARCH DIRECTIONS

Innovation management is a broad domain, and here, we systematically reviewed extant empirical literature relating DTs to marketing innovations. This focus is appropriate because marketing has been recognized (in addition to innovation) as an important engine for business growth, echoing Peter Drucker.

Research at the intersection between digital transformation and innovation management is still scattered. It lacks a unified perspective and overarching framework that can inform future theoretical and empirical studies as well as guide managers. This is due to the conceptual vagueness characterizing digital transformation and to the embryonic stage of development of scholarly research into this fascinating topic, which has dramatic practical implications.

This section offers directions based on our extensive literature review for advancing the interface between DTs and marketing innovation management. We provide recommendations for overall approaches to conducting additional research in this domain and some specific research questions that will help advance the discipline.

Categorizing digital technologies

Our research shows that academic researchers have used a variety of classifications to organize DTs. For example, some scholars have proposed descriptive categories, such as AI, big data, IoT, and smart products (Appio et al., 2021); Internet, mobile platforms, and social media channels (Flaherty et al., 2021); or 3D printing, augmented reality, AI, big data, blockchain, robotics, and social media (Rindfleisch et al., 2020). Others have proposed classifications based on the benefits of technologies, such as mechanical, thinking, and feeling, to classify a specific technology type (AI; Huang & Rust, 2021). Still others have classified technologies based on specific contexts, such as assisting, arresting, augmenting, and automating technologies in the human-machine interface context (Murray et al., 2021). Finally, some scholars have proposed classifications based on strategic objectives, such as supporting new forms of interaction between consumers and firms, providing new types of data that enable novel analytic methods, and developing marketing innovations (Hoffman et al., 2022).

These classifications are not mutually exclusive, and the elements are not necessarily exhaustive. For example, while Rindfleisch et al. (2020) consider robotics distinct from AI, Huang and Rust (2021) regard robotics as a part of AI. Furthermore, some classifications, such as those proposed by Huang and Rust (2021), cover only a particular technology (i.e., AI) and not others. Although these inconsistencies are inevitable at this emerging research stage, the lack of coherence in the underlying rationales and theoretical or managerial constructs behind the classifications makes it difficult to generalize across studies. As a result, marketing managers lack precise guidance on which technologies are effective for specific marketing innovation decisions. To address this research gap, we propose a new framework for classifying DTs in marketing. We believe that our typology provides a more parsimonious way to classify DTs in the context of the marketing function.

6.1.1 | Proposed 3As framework

A market orientation entails the generation of market intelligence, its dissemination, and responsiveness in marketing actions (Kohli & Jaworski, 1990). Recently, the rapid growth of DTs allows for massive amounts of data to be collected (e.g., clickstream data), sophisticated methods to analyze and interpret this data (e.g., text analysis), and the use of such analyses for decision-making by human beings as well as machines (e.g., self-driving cars, salespersons). We integrate the market orientation construct with the emerging capabilities of DTs to develop a 3As framework to guide the strategic use of DTs as they relate to marketing: data acquisition, data analysis, and data activation.

In our conceptualization, data can be in various forms, such as text, audio, and video. Data acquisition involves collecting information from entities internal or external to the organization (e.g., clickstream data to measure the frequency and duration of customer involvement on a website). In contrast, data analysis involves transforming and processing data to create insights that can potentially be useful for decisionmaking (e.g., using machine language modeling to determine the sentiment of online reviews). Data activation involves using the insights from data analysis to guide marketing actions (e.g., Uber's dynamic surge pricing).Table 2 presents our 3As framework for classifying DTs relevant to marketing. Because some technologies may be capable of doing more than one activity, i.e., data acquisition, analysis, and activation, for purposes of our framework, we classify the technologies based on their predominant capabilities. For example, machine learning models must read data input before analyzing it. Because data collection (based, for example, on customer or salesperson input) is of secondary importance compared to these models' ability to analyze the data to offer insights, we regard data analysis as the primary aspect of this technology rather than data acquisition.

Further, although there is little academic research on recent generative AI technologies such as ChatGPT, Google Bard, and MidJourney, our framework is flexible. It can be adapted as these technologies evolve in their capabilities and new technologies are introduced. As new information-management-related categories emerge, they can be added to the framework, and the location of existing technologies can be updated. This makes our framework a valuable tool for understanding and managing the ever-changing landscape of DTs.

6.2 | Understanding multiple impact pathways

Our review reveals four distinct but inter-related linkages between technology and marketing innovation: (1) the direct effect of technology on the marketer's action (e.g., targeted advertising using customer's prior behavior), (2) the direct effect on customer behavior (e.g., improving the user interface using chatbots and, thus, customer satisfaction), (3) indirect impact on the customer through the marketer's action as a mediator (e.g., reduced customer complaints as a result of a company's ability to solve routine problems using artificial intelligence), and

(4) indirect effect of the marketer's action on firm performance through customer behavior as a mediator (dynamic pricing increasing demand to bring in new customers). Several articles in the marketing domain examine the mediating effect of marketing actions. The technology–marketing interface provides a ripe opportunity to analyze and compare the different pathways by which technology can affect marketing and estimate the cumulative effect of technology in the different pathways.

6.3 | Understanding the process of how DTs impact marketing

Our review of the emerging literature shows that at this development stage of the research domain, many studies have focused on describing how technology can help marketing and if it can impact the firm and its customers. Most of these studies adopt a correlational design focused on the association between technology and outcome variables. However, for companies to make thoughtful decisions about investments in DTs, additional research is necessary on how technology influences managerial decision-making and customer behavior. For example, does technology enable faster decision-making, provide more collaborative decision-making, or both? Research emerging on crowdsourcing platforms for idea generation in the NPD process (Nam & Kannan, 2020) or remote meetings to facilitate team communication (Marion & Fixson, 2021) needs to be expanded to understand the role of these technologies in marketing strategy formulation and implementation. Similarly, does a user interface enable customers to reduce the consideration set to more relevant ones, or does it increase customers' flow state, resulting in increased happiness with the purchase process, or both? Such a nuanced understanding of the processes leading to the impact of technology will illuminate how organizations should implement DTs.

Developing broader impact measures

To extend extant research, future studies can explore additional dependent variables that marketing innovation can influence, such as firm survival and financial value. Beyond near-term sales, digital marketing tools can affect the level, speed, and volatility of future cash inflows and outflows and, therefore, customer lifetime value (CLV), net present value (NPV) of the firm, and stock market performances. Further, recently, there has been growing recognition that corporations should have a broader purpose. For example, Business Roundtable declared that "companies should serve not only their shareholders but also deliver value to their customers, invest in employees, deal fairly with suppliers and support the communities in which they operate."[2] The popular press and the academic literature are full of discussions on the broad-ranging impact of technology and its potential negative consequences. For example, Srinivasan and Sarial-Abi (2021) examine the role of algorithmic errors on customer response to brands.

Consequently, future research on the interface of technology and marketing should consider the impact on organizations, customers, and society. Managerial and policy decisions will ultimately depend on the weights put on these individual segments. These weights will be driven by the nature of the company and industry, the role of the government, public responsiveness to organizational actions, and other variables.

While firm performance and customer satisfaction measures are standard in the marketing literature, the broader impact measures on society are less prevalent. The role of technology in marketing is a prime candidate for pushing the boundaries by taking a more comprehensive view of the corporation. To do so, researchers should develop appropriate measures for the broader impact of implementing DTs.

6.5 | Examining separate and interactive technology effects

As our review indicates, DTs are continuously evolving. While diagnosing each technology's role is essential, understanding the relative impacts of different technologies and the interactive effects of multiple technologies is also important. This understanding will require largescale datasets so that appropriate statistical testing can be undertaken to measure various technologies' individual and collective impacts. Furthermore, these analyses should be complemented by field experiments to assess the exact role of different technologies accurately. As research proliferates in this domain, optimization models must be developed to help companies decide which technologies to deploy and, more importantly, how to allocate the technology budget across different technologies to obtain the greatest market impact.

6.6 | Investigating boundary conditions of technology's impact

More elaborate research designs may be required if the impacts of one or more technologies are context-specific. These contexts include the nature of the firm, industry, channel/platform, customer, and environment. For example, technology for buying utilitarian products may have different impacts than technology for buying hedonic products. The technology employed by individual airline reservation systems may have a different effect than the technology deployed by multisided platforms such as Expedia. Similarly, technologies deployed by highly regulated industries such as health care may have qualitatively and quantitively different impacts than those of less regulated industries (e.g., handyperson services). Research on the role of technology in marketing under various contexts is necessary for such a finegrained understanding.

While many studies have shown that DTs yield positive outcomes, some, such as Srinivasan and SarialAbi (2021) and Yang and Xiong (2019), argue that deploying DTs can backfire in specific situations. Given the increasing trend of using DTs as a marketing tool, further research on their potential negative effects would be valuable.

Focus on newer technologies

received increased academic attention and are widely acknowledged as particularly relevant. However, newer, emerging technologies such as blockchain and the metaverse have not received proportionate research focus compared with these technologies. Additional research is also necessary to enrich the understanding of the links among DTs, marketing process innovations, and outcomes. Extant literature has primarily emphasized the positive outcomes of DTs (e.g., customer purchase intention, firm sales). However, Luo, Tong, et al. (2019) note that humans are prejudiced against certain technologies (e.g., chatbots). Therefore, future research should investigate how the type of DTs affects outcomes and the boundary conditions of these links.

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TABLE 3 Specific research questions for future research.

6.8 | Exploring unknown and unchartered territories

Given the speed of the development of new technologies and the changes with each technology, organizations, individuals, and monitoring agencies need to develop sense-making abilities. In this vein, further research is necessary to address four sets of questions. First, are there likely fundamental shifts in consumer behavior and marketer decision-making? Second, given the rapid redistribution of advertising dollars from traditional television/print media to digital media, does the field need paradigm-shifting measurement methods to assess DT's impact? If so, how can firms estimate the need for marketing innovation professionals in various sectors? Third, as new positions, such as digital marketing experts and customer experience managers, become more common, how will marketing organizations and overall business organizational structures change due to DTs? Fourth, how should the convenience offered by DTs be weighed against customers' fears of technology taking over their lives and data privacy issues? These questions do not have easy answers, but the advancement of DTs in customer-facing marketing activities has brought these questions to the forefront. The COVID-19 pandemic has only made these questions more relevant for academic researchers and marketing managers to address. Furthermore, the recent popularity of generative artificial intelligence tools (e.g., ChatGPT, Google Bard, MidJourney) is already generating heated debates about their pros and cons and the appropriate and inappropriate methods of using these AI tools. Marketing applications of DTs will have to deal with these crucial questions – marketing actions may not only be governed by the ability of technology to accomplish things or what we “can” but also by ethical considerations related to whether we “should” use the technology and, if so, in which domains.

6.9 | Specific research questions

Emanating from the above discussion, we now focus on specific research questions. Rindfleisch et al. (2020) note that the proliferation of new technologies requires innovation scholars and practitioners to challenge existing assumptions, thereby offering opportunities to develop new knowledge. In particular, our review of the extant literature on DTs and marketing innovations suggests new topics and research questions (see Table 3) that provide a helpful starting point to guide further scholarly inquiry.

Consistent with our conceptual framework, these new questions focus on the firm perspective of marketing strategy and the customer perspective of the purchase journey, involve incremental examinations of issues, and take the research in radically new directions.

7 | CONCLUSION

Emerging DTs offer several significant opportunities for innovation, but studies linking these technologies and innovation are fragmented (Appio et al., 2021). Bresciani et al. (2021) state that even today, relatively little is known about how companies can implement digital innovation strategies for growth. Our research addresses this lacuna by mapping the landscape relating DTs to innovations in all marketing processes. Specifically, (1) we synthesize empirical research on DTs' role in marketing innovations, (2) propose a parsimonious typology to classify the benefits of DT to different aspects of marketing (3 As typology), and (3) offer several broad and specific directions for advancing research in this transformative domain. Our findings can spur further research on the capabilities that enable firms to gain advantages from DT-based marketing innovations and the consequent responses from competitors. Collectively, such investigations would offer a useful roadmap for firms seeking competitive advantage through marketing innovations by leveraging DTs.

Our review and analysis of DTs in the context of marketing innovations provide potential pathways for thinking about these critical and timely issues. Such a research endeavor would be further facilitated by stronger collaborative relationships among the following diverse entities: (1) academic researchers and universities, (2) professional organizations such as the Product Development and Management Association and Marketing Science Institute, (3) companies that generate massive volumes of data from customer participation (e.g., Meta, Google, Microsoft, and Amazon), and (4) business associations (Chamber of Commerce), governments, and transnational bodies (e.g., the European Union) interested in using research insights for managerial and policy decisions.

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