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Towards Human Digital Twins for Improving Customer Experience

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Completed Research Paper

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Abstract

Applications of digital twin (DT) technology have gained momentum in IS research and cognate disciplines. Several studies have documented how DTs create value in contexts such as manufacturing or smart cities through virtual monitoring and decision-making. While these contexts benefit from DTs of products or production steps, this research is the first to investigate the potentials of human DTs to improve customer experience (CX) (i.e., customer twins). Drawing on a structured literature review, we derive new conceptualizations of DTs as (i) virtual mirrors that depict a physical entity and its interactions in virtual space, and (ii) virtual orchestrators which extend the virtual mirror by also simulating potential virtual interactions. These new conceptualizations, by applying them to human DTs, enable us to discuss DT's implications to approach current CX potentials. The results of the discussion indicate that human DTs can support CX management to improve CX throughout the whole customer journey.

Keywords: digital twin, customer experience, customer journey, virtual mirror, orchestrator

Introduction

"Mirror, mirror on the wall, who's the fairest of them all?" – Though not being a physical mirror of objects, digital twins (DTs) are an uprising technology for virtual representations and have gained momentum in Information Systems (IS) research and practice (Dietz and Pernul 2020). In analogy to the mirror in Snow White, they might have more accurate answers to questions that could not be achieved in the real world, e.g., through data models that are not directly connected and synchronized with a physical object (Kritzinger et al. 2018). That is, paired with increasing computational power, DTs promise new methods of not only virtually representing, but also simulating the behavior of physical objects or subjects (Dietz and Pernul 2020; van der Valk et al. 2021). Initially introduced by Grieves in a presentation on product lifecycle management in 2003 (Enders and Hoßbach 2019), DTs were later described as a digital representation of a physical product, and thereby thought to mirror and predict behavior of physical products in a virtual environment (Grieves 2014). However, conceptualizing DT solely based on the functionalities of mirroring and predicting behavior in virtual environments does not allow distinguishing DT from related concepts, such as digital models, digital shadows, or digital threads (Kritzinger et al. 2018; van der Valk et al. 2021). Therefore, to distinguish DT from related technologies, the following definition aims to holistically cover the DT concept: *"The DT is a virtual construct that represents a physical counterpart, integrates several data inputs with the aim of data handling and processing, and provides a bi-directional data linkage between the virtual world and the physical one. Synchronization is crucial to the DT to display any changes in the state of the physical object"* (van der Valk et al. 2021, p. 3). Taken together, in contrast to the definition of Grieves (2014), the definition of van der Valk et al. (2021) additionally considers that (1) DT should rely on multiple data sources, bi-directional linkage, and ongoing synchronization between physical and virtual world to be more than just a mere representation of a physical object, and (2) DT is not restricted to a product but can be a twin of any physical object or subject, including humans (Enders and Hoßbach 2019).

The link from the DT back to the physical entity that it intends to mirror is often established by behavior simulation, and resulting decision recommendations (see, e.g., Kritzinger et al. 2018; Semeraro et al. 2021). These simulations have been applied in a variety of fields to improve decision making, including manufacturing (Greif et al. 2020; Ren et al. 2022), smart cities (Mohammadi and Taylor 2017), and aerospace (Tuegel et al. 2011), to name a few. Most of the applications for DTs are focused on designing new products or optimizing the design of existing products, or on monitoring and optimizing production processes and systems of critical infrastructures (e.g., smart energy systems) (Enders and Hoßbach 2019; Olivares-Rojas et al. 2021). The main goal of these DTs is to improve the physical entity with the ulterior motive to enhance customer experience (CX) (Semeraro et al. 2021; Tao et al. 2019). An ultimate short-coming of these implementations in the frame of CX is, however, that they consider product DTs which are limited to addressing those parts of the CX that are related to the direct interactions of customers with the product itself. Keeping in mind that CX in itself is a complex concept and emerges from highly individual customer journeys that can differ significantly between consumers (Lemon and Verhoef 2016), human DTs of customers may provide consumer-oriented solutions to improve CX on an individual level. However, DT conceptualizations of humans are rarely considered in research (Du et al. 2020), although a customer-centered focus on their interactions with such objects and systems, as well as the whole journey that goes beyond these interactions, may be more suitable to improve CX. Most of the conceptualizations of human DTs provided by the current state of research were developed for the healthcare context to improve therapy for patients (Barricelli et al. 2020; Elayan et al. 2021; Miller and Spatz 2022), which demands new conceptualizations of DT for its application in improving CX. Therefore, according to conceptualizations in healthcare literature, we see a *human DT* as representative of an individual human consumer.

Consequently, despite posing high potential to better create CX throughout the whole customer journey, an application of human DTs of customers is currently lacking in research. In line with this major research gap, current research lacks a conceptualization of human DTs, such as those of individual human customers. As CX is customer-centric, and thus, a human-centric approach to support value creation in complex consumption processes, a human DT might have even more potential to improve CX than DTs of single products or processes. Human DTs of customers could not only mirror, simulate, predict, and recommend behavior in line with customers' individual preferences and needs, but they may also allow integrated interactions between the physical and virtual space, and thereby, have substantial potential to enrich CX. This research therefore explores potential conceptualizations and roles of human DTs for CX. CX can be improved by managing the challenges that can arise in the multitude of a customer's interactions with firms throughout the stages of the customer journey (Lemon and Verhoef 2016). Thus, we relate the identified DT conceptualizations to customer journey stages to understand how human DTs can help managers overcome current CX challenges. Thereby, this paper addresses the following research questions:

RQ1: What conceptualizations can be derived for human DTs from the current state of the art of DT applications?

RQ2: How can human DTs help managers address current CX challenges throughout the customer journey?

Given that CX management is increasingly characterized by the use of technological innovations, such as artificial intelligence (AI) and Internet of Things (IoT), the following section introduces current challenges in CX research that have emerged or still remain after implementing these technologies. First, we derive the most recent CX challenges marketing managers are facing that may be addressed by human DTs. Second, we conduct a structured literature review on the current state of the art of DT applications in IS research. Based on this literature review, we elaborate new conceptualizations and roles of DTs, that are independent of the application area and the object or subject they represent, from a managerial perspective. We thus propose to apply these conceptualizations to the idea of human DTs. Our findings serve as a common understanding that can set the ground to examine the implications of human DTs for CX. In the discussion section, we then systematically discuss how far certain human DT conceptualizations can help managers overcome the identified CX challenges. Thereby, we illustrate the identified potentials with an exemplary smart city use case. Finally, we propose implications from our work that may inspire future studies to conduct empirical research on DT's potential for CX.

Current Challenges in Customer Experience Management

For the purpose of this research, we understand CX as a customer's internal and subjective response to any direct or indirect contact with a company (Meyer and Schwager 2007; Verhoef et al. 2009). Improving CX through the design of service processes represents one of the main tasks of the service design discipline, which is focused on designing the interactions between customers and service providers during the customer journey (Becker and Jaakkola 2020). However, technological advances, e.g., the proliferation of AI, IoT, and augmented reality (AR), have changed how customers interact with firms and services, thereby inducing new challenges for CX management (Hoffman et al. 2022; Kannan and Li 2017). Consequently, understanding how technologies can contribute to current CX challenges helps firms unfold the value propositions of new technologies such as DTs. In line with prior research on the role of new technologies in marketing (e.g., Davenport et al. 2020; Roggeveen and Sethuraman 2020), this research acknowledges the substantial potential of new technologies to benefit businesses, by improving customer awareness, engagement, or experience with products and services. Consequently, this research links DT conceptualizations with their primary influence on the customer journey. Generally, the customer journey can be conceptualized as "the process of experiencing service through different touchpoints from the customer point of view" (Kankainen et al. 2012, p. 221). While customer journeys in today's service landscapes are characterized by multiple touchpoints and stimuli (Becker and Jaakkola 2020; Lipkin 2016), broadly speaking, these touchpoints still relate to three stages: pre-purchase, purchase, and post-purchase. Following Lemon and Verhoef (2016) in proposing that each customer journey stage is characterized by certain customer behaviors, we relate each CX challenge to the managerial task that is focused on managing a certain behavior (e.g., search management addresses challenges associated with customers' search behavior). The behavioral orientation of the proposed framework enables us to provide recommendations for CX managers on how to address CX challenges by employing DTs. Next, we describe the most recent CX challenges that managers face in the era of digital technologies. In the discussion section, Table 1 provides an overview of the identified challenges, together with our derived implications of DTs to address them.

Customer Experience Challenges at the Pre-Purchase Stage

Needs management: Managers increase recommendation effectiveness by personalizing recommendations in line with a customer's needs (Bleier and Eisenbeiss 2015). However, a lack of data that informs personalization strategies can harm the CX. Imagine a customer for whom only the initial interaction with the firm has been observed (e.g., the first purchase). Firms would probably fail in personalizing the CX for this customer, referred to as the *cold start problem* (Padilla and Ascarza 2021). Moreover, personalization strategies lose their effectiveness the more time has passed since a customer's last interaction with a product or service. Specifically, when a customer has shown a certain behavior during the last online store visit, and this behavior is used for personalization of the customer's next visit, personalization can harm recommendation effectiveness (Bleier and Eisenbeiss 2015). Taken together, identifying and enabling the right degree of personalization represents a strong managerial challenge.

Search management: Customers engage in searching behavior to identify alternatives that satisfy their needs. Firms often support customers' search behavior through communication-based strategies, such as search aid provided by service staff. To make this communication more efficient, many firms increasingly replace human-based communication with AI-based machine agents, e.g., chatbots (Longoni and Cian 2022). However, customers may lack trust in these technologies. Longoni et al. (2019) provide support for this assertion, showing that trust in people is superior to trust in technologies. Therefore, anthropomorphizing technology appears a promising strategy (Seeger et al. 2021), as it offers the potential to nudge consumers toward greater self-disclosure by, for instance, transmitting social cues (Moon 2000).

Consequently, tactics that help managers in anthropomorphizing intelligence-enabled communication can positively affect the translation of consumers' search engagement into economic value for online retailers.

Consideration management: In today's marketplace, customers are confronted with a variety of new purchase channels and options (Wichmann et al. 2022). Therefore, reducing customer uncertainty during the consideration of multiple options represents a strong managerial challenge. AR is increasingly used in retailing contexts to enable "try before you buy" experiences. Prior research revealed that such virtual experiences are particularly effective when customers are uncertain about products (Tan et al. 2022), highlighting the potential value of AR technologies at the consideration stage. However, to provide value at the consideration stage, virtual CX should allow the customer to realistically evaluate whether the product of interest matches the intended usage (e.g., whether a virtually presented couch fits a customer's actual living room).

Customer Experience Challenges at the Purchase Stage

Choice management: Information overload can make customers stop searching and either complete or defer the purchase (Lemon and Verhoef 2016). Therefore, to counteract the ambiguity of purchase situations induced by information overload, retailers should aim to reduce the amount of information provided in purchase-related choice situations. Particularly online retailers should focus on selectively presenting individualized product information that enables a well-informed purchase decision based on the decision criteria relevant to the individual customer.

Ordering management: Great potential for *ordering management* comes from voice-based purchase tools. Online retailers increasingly employ in-home tools like Amazon's "Alexa" to make it easier for shoppers to complete purchases via voice-enabled ordering. However, as these technologies invade consumers' virtual and physical space (Cichy et al. 2021), ordering management demands new approaches for increasing trust in technologies' usage of personal data.

Pricing management: When customers show a general interest in products, *pricing management* can decide over a customer's decision to either complete or defer a purchase (Lemon and Verhoef 2016). At this stage, dynamic pricing strategies can deliver value for customers by serving price sensitivities that vary across customers and contexts (Villanova et al. 2021). However, managers' pricing decisions lack a database that serves the identification of prices that come as close as possible to consumers' willingness to pay (Haws and Bearden 2006), thereby limiting retailers' ability to maximize the profitability of customers' purchases.

Customer Experience Challenges at the Post-Purchase Stage

Service management: For customers who have completed a purchase, firms should establish infrastructures that enable more comfortable usage experiences. For instance, after buying a smart vehicle, it should track and analyze consumers' driving behavior in real-time to improve security based on analytical data models (Baesens et al. 2016). However, the explosive growth of intelligence-driven software applications has created data streams that capture how consumers think, feel, behave, and interact with products, services, other consumers, and firms (Wedel and Kannan 2016). As a consequence, consumers may worry about their privacy when using intelligence-driven services (Davenport et al. 2020; Martin and Murphy 2017). Thus, managers require technology-driven privacy protection to build trust with customers (Agarwal et al. 2020).

Consumption management: In the context of *consumption management*, AI enables task automation that can provide utility for customers (Davenport et al. 2020). Automation is often used in IoT tracking technologies. For instance, health wearables can provide value for a customer when they continuously monitor the customer's health state (James et al. 2019). However, customers sometimes resist automated features due to strong identity motives. For instance, when consumers strongly identify with driving cars on their own, they may resist automated driving features (Leung et al. 2018; Uysal et al. 2022). Therefore, managers require tools that help identify a degree of automation that is in line with an individual customer's preferences and motives.

Loyalty management: Creating a lasting digital relationship with customers has gained importance with the proliferation of engagement-based business models in digital services (Appel et al. 2020). As the revenue generated with these business models is proportional to the time customers spend with these services (i.e., engagement), loyalty strategies that keep customers engaged over extended periods become increasingly important. Prior research has shown that loyalty strategies are particularly effective when they dynamically adapt to customers' individual preferences (Siebert et al. 2020). For instance, many firms have started to implement game elements (e.g., points, levels) in their non-game services, referred to as *gamification* (Eisingerich et al. 2019). In gamified services, CX can be individually adapted to a customer's evolving skill levels. Accordingly, users that are more experienced with the app may need to complete more difficult goals in the app to achieve the associated reward (e.g., unlocking a new game level). We propose that such individualized loyalty strategies would benefit from increased data available about customers' individual preferences and behaviors. Zhang et al. (2019) provide initial support for the assertion that personalized CX can increase customer loyalty, showing that adapting the receipt of push notification to a user's engagement state can increase customer engagement and subsequently stimulate app revenues.

Method

Recognizing the limited availability of human DT conceptualizations in literature, we conduct a structured literature review of IS research by following the approach proposed by vom Brocke et al. (2009). As this method guides the reconstruction of accumulated knowledge on a specific topic, it is suitable for our goal to derive new conceptualizations of DT from the state of the art of DT applications (vom Brocke et al. 2009).

The IS relevance of the identified outlets was defined by using the litbaskets.io platform which provides an interface to filter an advanced Scopus search for IS relevant journals (Boell and Wang 2019). To avoid that a too narrow focus on the selected outlets weakens the generalizability of our findings, we selected the largest basket available on the website that includes 847 essential IS journals (to see a list of the journals selected, please visit the litbaskets.io website). Given that DT does not have a long research history, we extended the scientific outlets with papers identified in elementary IS conferences being ICIS, ECIS, AMCIS, PACIS, HICSS, and Wirtschaftsinformatik. In total, 853 publishing outlets related to the IS community were selected as sources. For all sources, we searched for the term "digital twin" without any further keyword restriction in the title, abstract, and keywords of papers. Given that the concept was introduced in 2003, we have included literature published as of this year. Figure 1 summarizes the applied procedure of the literature review.

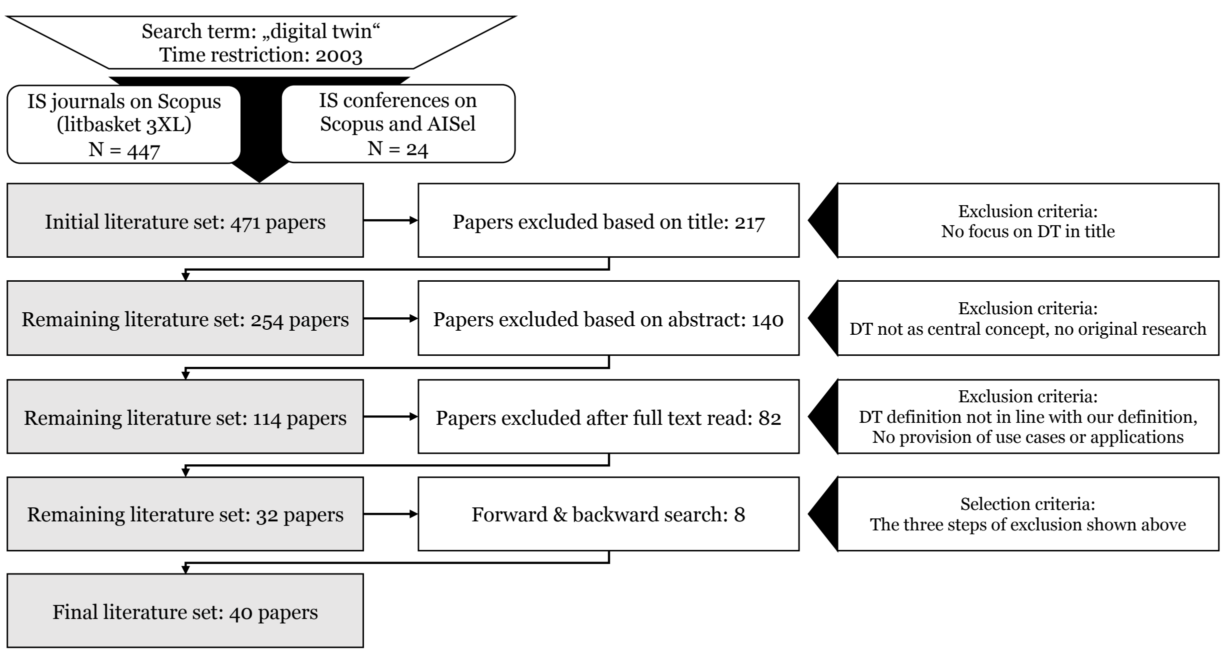


Figure 1. Overview of the Literature Review Process

As an initial search result, after eliminating duplicates, 471 papers emerged; 447 of which were identified in the IS journals, and 24 in IS conferences. Of these papers, 217 papers were excluded if the paper title did not directly include DT or a similar concept. Next, the papers' abstracts were reviewed to differentiate whether the paper is original research or a literature review. In case it was a literature review, the article was excluded. Next to this formal filtering step, we also excluded articles that did not have a clear focus on DTs (or CX). Through these two filter criteria, a set of 114 potentially relevant papers remained for full-text review.

For the full text, we excluded papers that did not provide use cases or applications of DTs, or which were not accessible through our institution. More precisely, we draw on our definition of DT stated in the introduction to determine whether a given publication is related to DT, or not. That is, the applied technology of identified literature needs to i) propose a virtual construct that represents a physical entity, e.g., assets, products, humans, or infrastructures (Enders and Hoßbach 2019), ii) integrate and synchronize various data sources for the purpose of data handling, storing, and processing, and iii) must include services which are provided by the virtual space as the application of a bi-directional linkage to the physical entity (e.g., behavior prediction, design optimization). As a result of this step, a pre-final set of 32 papers remained which were then used to conduct a forward and backward search in which the same exclusion criteria were applied. This led to a final sample of N = 40 relevant papers included in the analysis.

Results

For the purpose of deriving DT conceptualizations from a managerial perspective, we used a concept matrix to analyze the included papers. We extracted the following aspects from each publication: first, we identified how DT was defined and implemented (e.g., DT of a product assembly, the product itself, or the infrastructure of the firm?), and in which domain the DT was implemented (e.g., healthcare, or manufacturing?). Second, we identified the different goals, tasks and functioning of the DTs in the papers, depending on the specific domains and use cases (e.g., did the DT primarily predict product performance, coordinate other DTs, or provide treatment recommendations for patients?).

In a next step, we analyzed the extracted aspects and iteratively merged them into distinctive goals and functions of DTs at an abstract level that are independent of the application field and the object or subject they represent. From the results of this coding process, we finally derived two abstract "themes" of DTs that can be applied to all DTs from the dataset, serving as conceptualizations. That is, DT is seen both as 1) a mirror of physical interactions in the virtual world, and 2) an orchestrator of virtual interactions that are fed back to the physical entity in a continuous synchronization process. Both conceptualizations are inextricably linked and together define the DT. They are presented in detail in the following section.

Next to the conceptualizations of DTs, we identified through our coding process that DTs seem to take over different functional roles. As functional roles, we understand the overarching purpose assigned to the DT, bearing its application for improving CX in mind. In the second subsection of this chapter, we elaborate the two identified roles of DTs in detail.

Conceptualizations of Digital Twins

Digital Twin as a Virtual Mirror of Physical Interactions

As a DT integrates multiple data sources attached to its physical entity (Enders and Hoßbach 2019; van der Valk et al. 2021), it combines various digital references to create an overarching *virtual mirror* of its underlying entity (Dahmen and Rossmann 2021). Thus, one central characteristic of DTs is the liquification and density of information resources. In this regard, liquification describes the separation of information from physical objects and their transformation into information resources (Ng and Wakenshaw 2017; Normann 2001). Through liquification, a physical object's information is made available digitally and can be re-bundled to achieve maximum information density (Lusch et al. 2010; Normann 2001). Density in the context of information refers to the best combination of information resources to create value for a particular context, such as integrating data on the energy consumption and production patterns of different devices in a smart grid to provide services that enable optimization of energy flows (Olivares-Rojas et al. 2021). Next, we first consider use cases from the reviewed literature to derive our first conceptualization of DTs with the ultimate goal of transferring our conceptualizations to human DTs.

In the reviewed literature, DTs appear as the central technology to create information density, as they integrate a multitude of different liquified data sources to mirror a physical entity (Elayan et al. 2021; Lei et al. 2022). For example, a DT of a bridge can combine different data sources as separate digital representations, such as design parameters (e.g., length, mass, and concrete density) and context data (e.g., weather conditions, and traffic situation) to create a full real-time picture of the physical bridge (Kang et al. 2021). In this use case, information density increases through combining relevant data to support monitoring the health status of the bridge in real-time.

Besides depicting real-time data, the DT co-evolves with the physical entity over its entire lifetime. In the context of product design, DTs are used to enable a more informed, innovative design process for physical products. In the example of designing bicycles for a bike-sharing service, the DT collects design parameters of the bicycle as well as data gained from the bicycle's embedded sensors, such as the speed, acceleration, and wheel pressure (Tao et al. 2019). It also integrates environmental data and customer data over time, such as users' product and service reviews in the provider's mobile app, or physiological information like the customers' height distribution. The multitude of digital representations of the bicycle's use can be transformed into a comprehensive reflection of the physical product during its entire lifecycle. This reflection enables to gain comprehensive knowledge on the historic and real-time performance and need satisfaction for customers which can be used to enhance product design (Tao et al. 2019).

Further, the DT creates a digital replica of an entity through data processing. A healthcare use case shows how to combine mobile applications and sensors recording a patient's vital health parameters to create a virtual mirror of a real patient (Elayan et al. 2021). Specifically, digitally available data like the patient's genomics, demography, medical history, and contextual data like medication or crisis behavior can be integrated to achieve a high information resource density (Liu et al. 2019). The information gained from the mentioned physical objects' sensing technologies and digitized patient data uncovers different digital representations of a patient. The human DT, therefore, bundles and processes these representations to bring the patient "to life" in the digital world, creating a co-evolving virtual mirror. Based on this comprehensive picture of the patient, causal relationships can be better understood, i.e., the effects of external conditions (e.g., social factors, or weather) on patient behavior or the effects of particular medications and other treatments (Dahmen and Rossmann 2021; Liu et al. 2019).

Hence, DTs enable the depiction of a physical entity as a 'whole' through data integration and processing over its entire lifetime, which is more than the sum of its digital representations (Ng and Wakenshaw 2017). As the virtual mirror is able to process data internally, it can be clearly distinguished from synonymous terms, such as digital shadows and digital threads (van der Valk et al. 2021). However, the DT definition adopted in this paper requires a bi-directional data linkage. Thus, the conceptualization as virtual mirror represents the necessary precondition for enabling further virtual interactions in the digital world and providing feedback back to the physical twin. The corresponding conceptualization as orchestrator of virtual interactions is described next.

Digital Twin as an Orchestrator of Virtual Interactions

Drawing from the understanding that DTs condense information into a meaningful picture of the entity relevant to a particular context, the second conceptualization represents the notion that DT technology uses the created virtual mirror to enable value creation by extending the physical entity with digital services (Dahmen and Rossmann 2021; Tao et al. 2019). In this sense, the DT enables and coordinates virtual interactions such that they serve the overarching service goal, e.g., predicting product performance and adjusting product behavior (Tao et al. 2019), and influence the existence of the DT's physical entity. Thus, while the virtual mirror illustrates the real-world interactions of a physical entity, the orchestrator is able to act independently in the virtual world. The idea of the orchestrating role is inspired by the literature on platform economy and two-sided markets. In this context, orchestration is understood as the coordination of interactions between actors of two market sides (e.g., producers and consumers of products and services) to enable value creation (Boudreau 2017; Rochet and Tirole 2003). According to this view, the DT represents one side of the market as part of a set of exchange processes with other connected objects, customers, and systems, which in turn are participants of the other market side. More specifically, the DT may take on changing roles and act either as a consumer (e.g., a product receiving maintenance service) or as a producer (e.g., a product which is used by a customer). It orchestrates these exchanges with the overarching goal of creating value for its physical twin (e.g., improve its health status).

The use cases presented above clarify how the DT as an orchestrator of virtual interactions extends the virtual mirror. For example, based on monitoring the health status of a bridge, the DT can simulate potential virtual interactions (e.g., multiple overloaded vehicles on the bridge), and predict the bridge's stability for abnormal situations like earthquakes to develop maintenance plans (Kang et al. 2021). In the product design example, the digital reflection of a bicycle enables testing and simulating design decisions, thereby supporting the (re-)design of bicycles based on the customers' needs (Tao et al. 2019). Likewise, by creating a comprehensive digital copy of the patient, his/her health status can be monitored in real-time, and treatments can be tested and simulated in a safe environment to identify the right treatment. The DT can thus provide actionable recommendations for medication, surgeries, and patient behavior. The results of these actions in the real world can in turn be recorded and mapped in the virtual mirror for the purpose of gaining further insights about the patient (Dahmen and Rossmann 2021; Elayan et al. 2021).

Taken the conceptualizations together, the DT acts like a platform that 1) depicts and processes information about the physical twin's real-world interactions with its environment in the virtual space (virtual mirror), and in addition to this, 2) orchestrates interactions between this virtual mirror and its environment in the virtual space to create value for its underlying entity (orchestrator).

Functional Roles of Digital Twins

Digital Twin as a Virtual Decision-Maker

Given the presented conceptualizations, DTs can take on two different functional roles. In the physical world, interactions cannot be tested in the same way or not as efficiently as in a virtual world. In particular, the DT can orchestrate and test potential interactions and their outcomes in the virtual world to reduce uncertainties and risks of decisions in the real world. In such situations, the DT acts like a decision-maker which is exemplified in the following use cases.

A case study on thermal power plants considers a critical infrastructure that cannot be shut down and which is dangerous to be monitored and controlled on-site (Lei et al. 2022). Using DTs, operations, and behaviors of the physical plants can be simulated to predict failures in the process of energy generation. Based on these forecasts, system parameters can be reconfigured virtually to improve the plant's performance and health status. Moreover, operations in the physical system that are too dangerous for employees can be conducted through the DT, while ensuring the safety of themselves and the physical equipment (Lei et al. 2022). Further, many connected systems, such as industrial control systems or smart grids, are increasingly targeted by cyber-attacks and taking them offline to investigate and model attacks are often expensive or not feasible in operational environments. DTs can be used to virtually identify and predict cyber-attacks and perform corrective actions. Thereby, safe operations can be ensured while avoiding system stops and shutdowns (Olivares-Rojas et al. 2021).

In the case of personalized healthcare solutions, the patient DT can orchestrate and test different medications and surgeries in the virtual world to provide professionals with recommendations for treatments with the best curing outcomes in real life (Elayan et al. 2021). By predicting rain forecasts and corresponding effects on the water level, a wetland DT can virtually test regulation mechanisms and provide action recommendations to stakeholders to regulate the water level of a physical wetland (Aheleroff et al. 2021). As depicted in Figure 2, the DT acts as a virtual testing platform and enables to solve complex decision problems to influence its digital self in a simulated environment and finally feed these outcomes back to create value for the physical entity (Dahmen and Rossmann 2021).

Even though the DT serves as a decision-maker for a physical entity, a physical object or subject does not necessarily need to exist before the processes of conducting testing and simulation. In product development scenarios, virtual prototypes are first created and simulated in external simulation models. These models are incorporated into the final product which is then linked with the virtual entity to form a DT (Dahmen and Rossmann 2021). Regardless of whether the digital or physical twin exists first, synchronization between the two forms a closed-loop throughout the entire lifetime of the entity (Dahmen and Rossmann 2021; Khan and Pigni 2021). Hence, DT technology supports decision-making on products through orchestration across different steps of the product lifecycle. Dynamic innovation can be enhanced by incorporating customer requirements in the design process and verifying the performance of a product through simulation. Furthermore, virtual orchestration can enhance dynamic control and optimization of manufacturing processes, fault prediction, and recycling processes (Ren et al. 2022).

DTs are also widely used to orchestrate and coordinate interactions between other DTs to achieve macro-level goals on a system level that go beyond decision problems of individual entities. For example, to synchronize IoT devices, that are impaired in communicating within industrial networks due to temperature-induced clock drift, DTs of each clock enable to predict effects of environmental factors on clock behavior. A system twin can be used to orchestrate the interactions between IoT devices based on these outcomes for situation-aware synchronization (Jia et al. 2021). A further example is found in unmanned aerial vehicles which do not have the computational capacity to process sensor data (Lei et al. 2021). DTs could reflect and predict the lifecycle of entire swarms and provide optimal decisions for swarm cooperation on various tasks, such as a swarm trajectory program and cooperative target search. In this case, each vehicle is represented by its own DT. Different interactions among these twins and their outcomes are simulated to find decisions for complex problems of swarm cooperation (Lei et al. 2021). In the context of smart cities, city DTs are used to support disaster response and human relief actions (Fan et al. 2021). As a multitude of actors with different individual goals, interests, and knowledge participate in decision-making in smart cities, the outcome of certain decisions is based on various factors and uncertainties. DTs enable to identify and evaluate coordination strategies among decision-makers based on simulations of the predicted effects of particular decisions on other actors and the city in the case of disasters (Fan et al. 2021). Thus, systems of DTs enable to find optimal solutions for complex problems on a system level, while at the same time not impairing the outcome for the single entity twins.

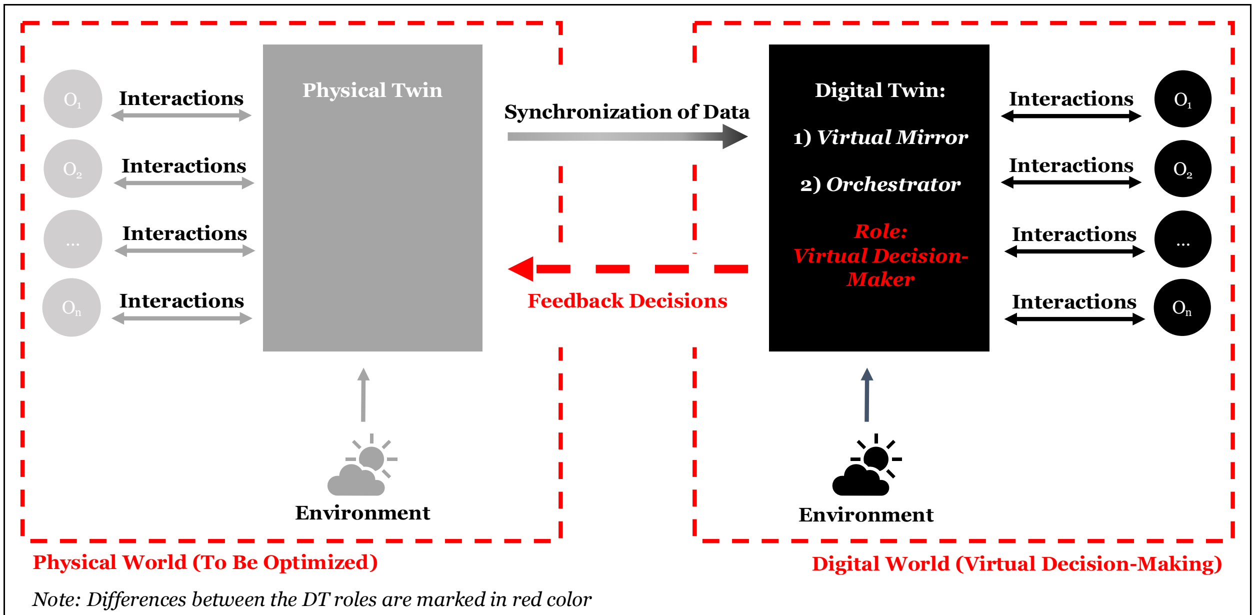
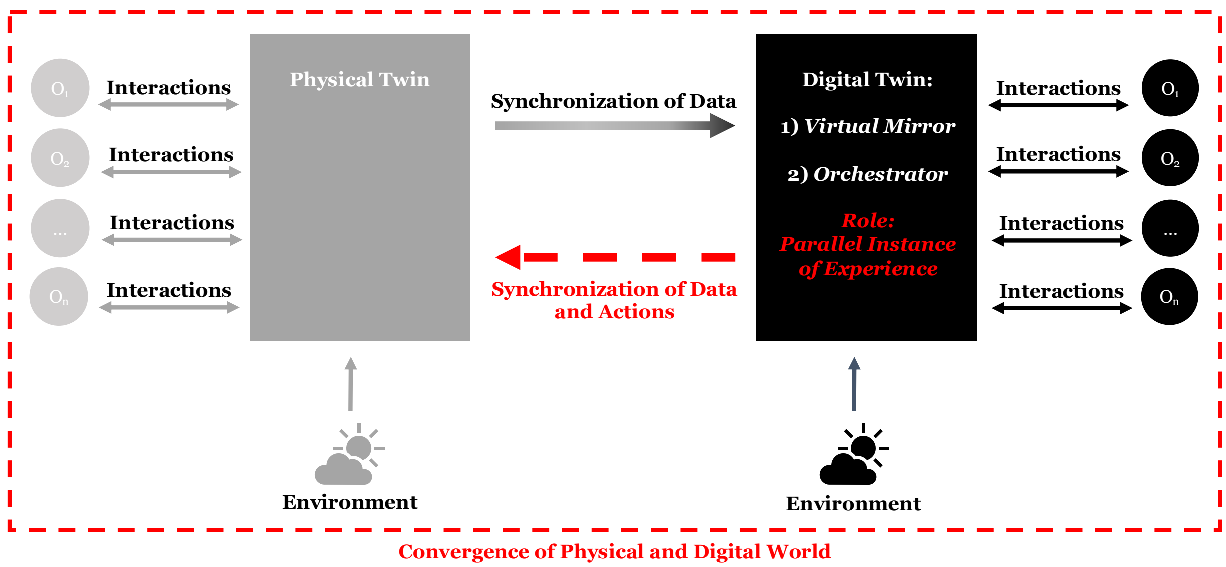


Figure 2. DT as Virtual Decision-Maker

Digital Twin as a Parallel Instance of Experience

Besides serving as an external simulation instance that orchestrates potential interactions in the virtual space to solve problems for the physical twin, a DT can also take on the role of a parallel experience instance. As such, the relationship between the two twins is not hierarchical in the sense that the DT serves as a testing instance for the physical twin. In contrast, the DT enables an extended experience of the physical entity, which can be equally accessed in the virtual world (see Figure 3). Interactions of both the physical twin and the DT are orchestrated and processed virtually and continuously synchronized to create a convergence between the two worlds. Thus, the twinning entity can be accessed, used, and experienced simultaneously on-site and remote.

An illustrative example is virtual visitation of social events, such as concerts, museums, and expositions (Riemer and Seymour 2021). DTs of such events reflect digital replicas of the event space and its main features, enabling visitors to be present with their digital avatar in a spatial and socially engaged experience of virtual attendance. Users can interact with the digital event space, event activities, and even with other visitors. Spatial presence in the digital world can be achieved by virtual walk-throughs that offer the user to explore the digital environment through VR technology. It can be extended using haptic VR controls which enable the users to actively manipulate and use objects. On this level, the spatial DT orchestrates the user's interactions with the digital environment and conducts real-time synchronization to implement their outcomes in the physical event space. Similarly, users can experience social presence by communicating with other visitors via text, chat, or natural language and facial expression simulations. Communication across physical and digital spaces can be realized via touchpoints in the event space acting as devices where hosts, guides, and visitors can interact with each other. By creating a DT of a social event, further services can be provided to visitors that improve and extend the event experience. For example, users could be enabled to record their movements and journeys to revisit their favorite places, receive recommendations for guided tours as well as find and meet their personal networks (e.g., friends, business contacts) within the event space (Riemer and Seymour 2021). As a parallel instance of experience, DTs contribute to enriching CX through a convergence of the physical and digital (and in the given example even the social) worlds of the customer (Bolton et al. 2018).



Note: Differences between the DT roles are marked in red color

Figure 3. DT as Parallel Instance of Experience

Discussion

The presented conceptualizations serve as a common ground for understanding DT from a managerial perspective. We propose that our concept of DT can be applied to human DTs of individual customers to improve CX. Therefore, in this section, we first describe the idea of such human DTs, and secondly, derive potential implications of human DTs for CX, considering how they can address the CX challenges (see background section). Table 1 gives an overview of the challenges and the identified DT implications.

The human DT serves as a platform on which a combination of different embedded technologies, such as IoT, and AI (Khan and Pigni 2021) are used to collect, process, and orchestrate data and interactions referred to a specific customer, providing a bi-directional data linkage between the physical and digital world. We argue that this combination of technical solutions, bi-directionally connected to the customer throughout her/his lifetime, creates a truly complete picture of the customer, as opposed to existing standalone solutions, and thus enables highly individualized CX design. Referring to our first conceptualization, the DT bundles relevant interactions of the real customer with products and services to increase information resource density to create a comprehensive virtual mirror of the customer. Additionally, the DT can be provided with contextual data from the customer's environment (e.g., from social relations) and further personal data (e.g., demographics). Thus, the virtual mirror enables understanding the customer's behavior as more than the sum of its digital representations. As an implementation of the second conceptualization, the human DT integrates not only real interactions conducted by the customer in the physical world but also orchestrates virtual interactions and contextual parameters to support simulation-based decision-making for CX or to create parallel instances of experience. To discuss potential implications for CX along the customer journey in the following subsections, we illustrate improvements in the CX considering an exemplary smart city use case. Specifically, we consider a scenario, in which the commercial activities of a customer (e.g., consumption of services) in the city are considered from the perspective of a holistic CX which is characterized by continuous value-creating interactions between a customer and the multitude of smart city actors she/he interacts with (Muschkiet et al. 2022).

Pre-purchase stage: companies could draw on a wide-ranging virtual mirror of the customer. The human DT could provide computing and data processing capacities to companies that lack corresponding resources and competencies. As such, the DT could support firms in analyzing and predicting customer behavior. Specifically, companies could access historical data on the customer's purchasing processes with other firms (e.g., in a city) to solve the cold start problem. In a similar vein, firms could use data of other customers that show characteristics similar to the targeted customer (e.g., comparable product preferences or inter-visit-times) that is also stored in the DT. These data can enhance predictions about the customer for whom the firm has limited access to data sources that have high predictive validity. *Needs management* can be supported by the virtual mirror examining customer reactions, such as emotional responses, to historic and current personalization activities to find the right personalization degree. By receiving feedback on current activities in real-time, the success of personalized services may be evaluated continuously. Moreover, instead of estimating customer needs based on statistical profiles and comparisons among large sets of similar customers, market uncertainties could be reduced by identifying causal relationships for individual customer behavior (e.g., a customer prefers to go to the office by car instead of a sharing bike on Tuesdays, due to an early regular appointment). Furthermore, when acting as an orchestrator, the DT could help predict the likelihood that a customer will accept certain recommendations or consume other personalized services through a simulation of customer behavior depending on dynamically changing contextual factors. For example, preferences for sustainable transportation means can be combined with predicted contextual factors, such as the customer's appointments and future weather conditions, to provide an individualized recommendation for a bus ride or a bike-sharing offer. If the whole prediction process is linked with a real-time updated database and intelligent algorithms that search for repetitive patterns and causal relationships, firms can even automize personalized recommendation strategies. In *search management,* a comprehensive understanding of behavioral responses through the virtual mirror could enhance the detection and solving of trust issues according to technology-based communication means. For example, chatbot communication can be adapted and anthropomorphized by predicting emotional responses to certain communication schemes, using the DT as an orchestrator, and comparing them to historic communications with human personnel. In *consideration management*, the orchestrator can make AR experiences more vivid by providing the customer with a parallel experience instance for product testing. Products could be tested virtually based on the customer's physical characteristics as an equal experience compared to testing them in the real world. For example, customers could try on clothes available in a store in the city with the help of DT-based simulation. Without the hurdle of putting them on in the physical store, customers can assess the individual fit from home and receive automated feedback, such that the DT could even replace sales personnel.

Purchase stage: the DT as a virtual mirror can support *choice management* by analyzing the customer's cognitive load when processing information provided on products, services, and alternatives. For example, a cognition model could be developed in the virtual mirror based on initial neuroimaging tests (Du et al. 2020). Then, a customer's cognitive status could be predicted through orchestration and testing of different information sets. Thus, the DT as an orchestrator can help firms identify the right amount of information to serve the customer. In *ordering management*, using the orchestrator as a personal data management agent who gives firms access to customer data based on the customer's data-sharing preferences could increase the customer's trust in a firm's privacy practices. Thus, the customer could give action instructions to the DT on which information can be shared with certain firms in the city. Firms could also automate this process by allowing DTs to transfer customers' data restriction decisions in one application (e.g., a car-sharing app learns a customer's preferences for sharing location data in transportation contexts) to restrictions in similar applications (e.g., location data sharing in a bike-sharing app). Serving as a centralized customer data platform, DT could even contribute to restructuring market mechanisms in the trade of data in such a way that customer data can be sold to companies via DT as an orchestrator. The DT would then serve as an automated broker who sells the customer's data to firms based on his/her preferences. The DT can also provide monitoring services by giving access to the synchronized virtual mirror of the customer. For example, the effects of data sharing on receiving useful recommendations and information could be visualized on a dashboard to give the customer, but also firms, feedback on how the personalized offers have influenced his/her actions in the city. Furthermore, in *pricing management*, with a DT that reliably predicts a person's situational activities and needs, it is also possible to increase the accuracy of the prediction of willingness to pay. Knowing the routines of a customer, the DT as an orchestrator enables to predict his/her actions based on situation-aware simulations. For instance, when a customer is walking through a high street and rain is predicted, the customer could be notified of an individualized discount on an umbrella offered at a nearby store.

Post-purchase stage: *service management* and its infrastructures could be improved by using the virtual mirror as a central customer account that ensures controlled access to all networked services that require registration, thereby enabling single sign-on through bundling different accounts for various services. The customer could enjoy a seamless experience in the city through an automatic login and authentication through the DT as an orchestrator when using car-sharing offers or performing administrative tasks in the citizen's office. Data emerging from the customer's interactions connected to different accounts as virtual identities are automatically synchronized and integrated into the central virtual mirror. Further, the DT can also support task automation in *consumption management*. An automated parking assistant, for example, could receive action instructions on the optimal level of automation, which the DT determines based on the orchestration of current contextual factors and a prediction of the customer's cognitive load and automation preferences. In addition, real-time observation of a customer's consumption behavior enables to enhance *loyalty management* by applying situation-aware gamification and loyalty strategies through the DT as an orchestrator. In this way, climate-friendly customer behavior, such as driving through the city with an electric car, could be rewarded. For example, discounts on the next electric charging station could serve as situational offers that increase customer loyalty.

Besides the three stages discussed in this section, literature has recognized that the customer journey is an iterative and dynamic process, incorporating previous and past experiences (Lemon and Verhoef 2016). Reinforced by the increasing connection of products and digital services, today's service landscape is rarely limited to dyadic relationships between customers and single firms. In contrast, CX emerges from a variety of value-creating interactions of customers with multiple actors in complex service systems (Becker and Jaakkola 2020). For example, customers living in smart cities can consume and co-create services at multiple touchpoints provided by different actors (Lipkin 2016). Each of these services and their individual experiences contribute to an integrated holistic CX in the city (Muschkiet et al. 2022). However, a lack of collaboration across different firms, e.g., in sharing data for service design, poses challenges to creating such a holistic experience (Muschkiet et al. 2022). Thus, enhancing CX requires increasing collaboration among firms, even across different industries, to integrate the stages throughout the customer journey, as well as previous and following experiences (Lipkin 2016).

In terms of integrating consecutive journey stages and individual experiences to improve the overall CX, the DT offers the potential for continuous value creation across the boundaries of single firms' activities. Behavior analysis through the virtual mirror offers companies the opportunity to identify the customers' needs across all their activities and to collaborate to improve the overall CX. This knowledge helps link experiences and play out suitable offers for customers at short notice through the orchestrator, thus giving customers what they need when they need it. In the smart city use case, a customer's shopping activities could be linked with optimized mobility solutions to improve the customer's overall shopping experience. In addition to personalized recommendations for products offered in the city, the DT could suggest the best possible route and suitable transport offers to get to a shopping destination, considering both individual preferences and the current traffic situation. Imagine a customer preferring to take an own electric vehicle when it is raining, charging stations would then generate individualized customer value by recommending individualized prices. If the DT observes that the customer is charging his/her car at the suggested station, it can play out action recommendations to a nearby café to offer the customer promotion for a drink. Expanding this view to a perspective of multiple customer DTs connected in a multi-customer-DT system, a system DT can serve as a platform that orchestrates potential decision solutions of each twin to achieve goals on a macro level (e.g., on a societal level). For example, by simulating the effects of DT activities of one customer on the performance of people, objects, processes, and infrastructure in his/her surrounding, the impacts on other customers' experiences can be predicted. In a smart city mobility scenario, digital customer twins and DTs of cars and traffic infrastructure can cooperate on a system-level DT to improve the mobility situation for all customers in the city. Taken together, in accumulating individual-level customer value, DT also can contribute to macro-level goals, such as sustainable city development or improvements in city security.

	Managerial Task	**Current CX Challenges**	**Implications DT as Virtual Mirror**	**Implications DT as Orchestrator**
Pre-Purchase Stage	Needs Management	• Inaccurate needs predictions due to limited customer-firm interaction data ("cold start problem") • Over-personalization or lack of personalization of recommendations	• Uncover causal relationships of customer behavior • Evaluate and adapt personalization strategies through real-time behavior monitoring	• Predict the success of personalized services through response simulation • Automate personalization activities and recommendations
	Search Management	• Inferiority of technology-enabled communication (e.g., chatbots) compared to human communication	• Detect trust issues based on emotional responses	• Adapt and anthropomorphize communication through simulating emotional responses to communication schemes
	Consideration Management	• Lack of vividness of virtual experiences (e.g., AR)		• Customized testing of products in virtual environments
Purchase Stage	Choice Management	• Limit information and/or option overload	• Analyze cognitive loads in different information scenarios	• Predict personalized information amounts through cognitive load simulations
	Ordering Management	• Lack of trust in privacy-invading ordering technologies	• Monitor effects of shared customer data through personalized dashboards	• Customer-oriented data management and automated cross-application transfer of customers' data restrictions • Customer-oriented broker for data sharing/selling
	Pricing Management	• Imprecise dynamic pricing	• Discover individual effects of contextual factors on willingness to pay	• Improve pricing accuracy through situation-aware prediction of willingness to pay
Post-Purchase Stage	Service Management	• Disjointed infrastructures interrupt the CX • Lack of trust in intelligent services/ communication	• Centralized user account which integrates customers' interaction data	• Automated log-in and authentication for multiple services through a central single sign-on
	Consumption Management	• Find the right degree of task automation		• Personalized task automation through situation-aware prediction of preferences and cognitive load
	Loyalty Management	• Individualize technology-enabled loyalty strategies (e.g., gamification)		• Situation-aware gamification and loyalty strategies

Note: The implications are classified by the conceptualization in which they have the most influential role. As both conceptualizations together define the DT, many implications apply to more than one conceptualization.

Table 1. DT Implications for Current CX Challenges throughout the Customer Journey

Conclusion and Outlook

DT technology has gained increasing attention in IS research and related disciplines. Literature has examined the DT's potential in supporting various decision problems, such as improving the design and health status of products and infrastructure, or processes in manufacturing or energy systems. While these objects mostly influence the experience of the customers using them, prior research does not offer a systematic examination of how DTs can support CX. As CX is customer-centric, and therefore human-centric, we suggest that human DTs applied to individual customers might have even more potential to enhance CX, compared to single products and processes focused on by most of the prior literature. Therefore, through an explorative structured literature review on chosen DT applications in IS research, we derived the following new DT conceptualizations which we propose to apply to the idea of human DT: (i) DT as a virtual mirror that comprehensively depicts a physical entity's interactions in the virtual space, and (ii) DT as an orchestrator which builds on the virtual mirror to further simulate virtual interactions which have not yet taken place. In addition, we identify that DTs can take on different functional roles, i.e., serving as a virtual decision-maker or a parallel instance of experience. Based on these insights, we discuss how human DTs of customers, as virtual mirrors and orchestrators, can help to solve current CX challenges.

With our conceptualizations and the derived implications, our work makes the following contributions to the state of the art of DT literature: (1) We present new conceptualizations and roles of DTs from a managerial perspective. In this way, we provide a common understanding of the technology that serves as a basis to relate DTs to CX and its management; 2) We adapt these conceptualizations to the idea of human DTs of individual customers, for which suitable concepts have not yet been sufficiently developed and investigated for CX and related customer-oriented approaches at the intersection of service science; (3) We identify a set of potentials of human DTs that could help overcome current CX challenges throughout the customer journey. These potentials can serve as indications for empirical research on human DT applications and their effects on CX. From a practical point of view, the identified functional roles provide managers guidance on potential application scenarios in which human DTs can create value. By understanding human DT from a platform perspective, our conceptualizations make its implementation tangible in the context of CX management. Further, based on the implications of human DTs elaborated in this paper, managers can develop approaches that use DT technology to address current CX challenges.

Finally, future research should consider conducting structured interviews to derive CX challenges and to validate the identified potentials of DTs to improve CX, especially in comparison to existing technologies. Further, research could develop suitable concepts for human DT implementation with the purpose to improve CX. Based on our findings, we call for further examinations on how the identified potentials can be realized in human DTs. As an extension of our work, drawbacks, and challenges associated with the use of DT to improve CX should be investigated (e.g., customer privacy issues, companies' unwillingness to share customer data with other companies or identifying the opportunities and boundaries of data collection and usage for specific application scenarios of DTs). In addition to human DT improving CX for individual customers, future research should examine the potentials and implementations of DT systems that integrate multiple customers. Specifically, studies could investigate how coordination among a set of different DTs can be optimized to improve CX for multiple customers or achieve further macro-level goals, such as sustainable city development. Addressing the proposed research gaps will help firms, customers, and society unfold the value propositions of DT.

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