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Abstract:

Digital technology (DT) is creating and shaping today's world. Building on its identity and history of technology research, the Information Systems discipline is at the forefront of understanding the nature of DT and related phenomena. Understanding the nature of DT requires understanding its purposes. Because of the growing number of DTs, these purposes are diversifying, and further examination is needed. To that end, we followed an organizational systematics paradigm and present a taxonomic theory for DT that enables its classification through its diverse purposes. The taxonomic theory comprises a multi-layer taxonomy of DT and purpose-related archetypes, which we inferred from a sample of 92 real-world DTs. In our empirical evaluation, we assessed reliability, validity, and usefulness of the taxonomy and archetypes. The taxonomic theory exceeds existing technology classifications by being the first that (1) has been rigorously developed, (2) considers the nature of DT, (3) is sufficiently concrete to reflect the diverse purposes of DT, and (4) is sufficiently abstract to be persistent. Our findings add to the descriptive knowledge on DT, advance our understanding of the diverse purposes of DT, and lay the ground for further theorizing. Our work also supports practitioners in managing and designing DTs.

Keywords: Digital Technology, Information Technology, Purpose-related Classification, Taxonomy, Taxonomic Theory, Cluster Analysis.

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1 Introduction

Today's world is unimaginable without digital technology (DT). Individuals and organizations participate in countless sociotechnical systems (Mousavi Baygi, Introna, & Hultin, 2021; Tilson, Lyytinen, & Sørensen, 2010), in which DT supports or enables, among others, mobility (D'Mello & Sahay, 2007), interconnectivity (Sandberg & Tsoukas, 2020) and virtuality (Schultze, 2014). As a result, novel DT-driven opportunities emerge with enormous potential from an economic (Legner et al., 2017; Oberländer, Roglinger, & Rosemann, 2021) as well as a societal perspective (Briel et al., 2021; Kreuzer, Lindenthal, Oberländer, & Röglinger, 2022; Tim, Cui, & Sheng, 2021). However, in a society where DTs are essential mediators of reality (Baskerville, Myers, & Yoo, 2020), the economic and societal transformations induced by DTs are far from being complete. Given DT's central role representing, creating, and shaping reality, understanding its nature is of crucial importance for research and practice alike.

The DT construct has evolved from a rich body of knowledge on the nature of technology, to which the Information Systems (IS) discipline has contributed significantly. To name but a few, Kline (1985) addressed the fundamental question of "what is technology" (p. 1) and uncovered that understanding technology depends on its purpose in different contexts, i.e., as an element of sociotechnical systems. Orlikowski (1992) provided a conceptualization of technology, where she unfolded its duality as something that can be a product and medium of human actions as well as something that can be institutionalized in an organization. IS research has always put technology at its center (e.g., Hirschheim and Klein (1989) and Klein and Hirschheim (1989)) where information technology (IT) represents the central component of information systems (Davis, 2000). IT is defined as the use of technology as a collector, storage, processor, and transmitter of information and covers a digital and a physical perspective (i.e., soft- and hardware) (Boaden & Lockett, 1991). Starting as a mere tool separated from individuals and their work (El Sawy, 2003), over time, IT has evolved into an integral component of products, services, and individuals' lives, which broadened the understanding of IT putting more emphasis on its digital characteristics (Kallinikos & Mariátegui, 2011; Tarafdar & Tanriverdi, 2018). As a result, the term DT emerged referring to technology that is embedded in products and services and can hardly be disentangled from the underlying IT infrastructure (Henfridsson & Bygstad, 2013; Yoo, Henfridsson, & Lyytinen, 2010).

Since then, DT has become one of the core research constructs in multiple IS research streams which focus on DT-related phenomena such as digitalization (Caputo, Pizzi, Pellegrini, & Dabić, 2021; Legner et al., 2017), digital transformation (Gimpel et al., 2018; Vial, 2019), digital innovation (Ciriello, Richter, & Schwabe, 2018; Nambisan, Lyytinen, Majchrzak, & Song, 2017), and digital entrepreneurship (Briel et al., 2021; Kreuzer et al., 2022). Furthermore, considerable effort has been put into extending our understanding of the nature of technology in digital contexts by studying digital objects and artifacts. Faulkner and Runde (2013, 2019) presented a theory of digital objects, i.e., "objects whose component parts include one or more bitstrings" (Faulkner & Runde, 2019, p. 1285). Moreover, Kallinikos, Aaltonen, and Marton (2013) presented an ambivalent ontology of digital artifacts and Ciriello, Richter, and Schwabe (2019) studied paradoxes of digital artifacts usages in innovation practices. To delineate digital objects from DT, most recently, Hund, Wagner, Beimborn, and Weitzel (2021) refined the definition of DT outlining that a "[…] digital object becomes a digital technology when it is assigned a meaning, namely a purpose for applying it […]" (p. 5). Along these lines and closing the loop back to Kline's (1985) work, connecting DT and purpose has a long history in research. The understanding of DT depends on its purpose in different contexts (Ciriello et al., 2019; Kline, 1985), whereby purpose relates to the social positioning of a DT within a sociotechnical system, e.g., related functions, and associated rights and responsibilities (Faulkner & Runde, 2019). Essentially, the purpose of a DT is determined by the social actors using it (Hund et al., 2021).

Following these important insights, it becomes obvious that understanding the nature of DT is closely related to understanding the purpose of DT within a social context. However, owing to its embeddedness in products and services and its immersive role in sociotechnical systems, DT is associated with manifold purposes today, such as data collection, insight generation and interaction (Bharadwaj, El Sawy, Pavlou, & Venkatraman, 2013; Pavlou & El Sawy, 2010). To avoid being overwhelmed by the growing number and high diversity of specific DTs, IS researchers would benefit from a useful classification of DTs through their purposes in order to describe, understand, and analyze DT more effectively (Gregor, 2006; Kundisch et al., 2021). While current research already provides valuable and mature knowledge on the nature of DT (see Section 2 for details), existing classifications do not account for the variety of DT purposes in a way that (1) has been rigorously developed, (2) accounts for the characteristics of DT, (3) is sufficiently concrete to appropriately reflect the diverse purposes DT, and (4) is sufficiently abstract to be persistent (over a reasonably long period of time). First, for example, professional trend reports, such as the Gartner Hype Cycle for Emerging Technologies (GHC), include lists of technology names mapped to cycle phases, however, without empirically validating results or providing insights into technology purposes. Second, existing approaches do not focus on DT or specifically consider (digital) characteristics of technology as they were built for similar but not synonymous constructs, e.g., Davis's (2000) classification of (traditional) IT. Third, existing classifications barely substantiate DT purposes. Related studies often name purpose categories as a component of their definition of DT. Further elaborating on them is not their primary focus (e.g., Vial (2019)). For example, Bharadwaj et al. (2013) defined DT as a combination of information, computing, communication, and connectivity technologies, where neither of these purposes nor possible combinations are specified. Fourth, existing approaches focus on one or a sub-set of DTs and are hence not useful for providing a holistic overview of DT purposes, e.g., van der Valk, Haße, Möller, and Otto (2021) focusing on digital twins.

Against this backdrop, we argue that a useful classification of DTs through their purposes (henceforth: purpose-related classification) will not only serve scientific progress but be also relevant in practice. On the one hand, a purpose-related classification would enable us to abstract from individual DTs when studying or theorizing related phenomena and, instead, focus on selected types of DTs sharing the same purpose. Further, such a classification would provide initial insights on an emergent DT by classifying it through its purpose. On the other hand, when taking DT decisions in practice, managers are currently left alone with the diversity of DTs (Adomavicius, Bockstedt, Gupta, & Kauffman, 2008), usually aiming to make specific DT decisions late in product development or process redesign initiatives. A purpose-related classification of DTs would support managers in the structured assessment and selection of the growing number of DTs as part of strategic initiatives. At last, researchers and practitioners alike could leverage a purpose-related classification for the design of novel DTs that address existing purposes better than others or create new purposes. Thus, to advance our understanding of the diverse purposes of DT, to facilitate further theorizing around DT, and to support practitioners in managing or designing DT, we ask:

How can DTs be classified through their purposes?

To address this question, we build a taxonomic theory (Gregor, 2006) for DT that enables its classification through its diverse purposes. We follow McKelvey's (1982) 'organizational systematics' paradigm and develop two artifacts that make up our taxonomic theory: (1) A taxonomy of DT and (2) purpose-related DT archetypes. First, we describe differences and commonalities of individual DTs by developing a multi-layer taxonomy for individual DTs according to Nickerson, Varshney, and Muntermann's (2013). Hund et al. (2021, p. 5) made the case that purpose "is determined by social actors such as users". We therefore argue that the purpose of DT is something that can be studied best by analyzing DTs close to practice. Hence, our taxonomy development approach builds on a sample of 92 real-world DTs compiled from the GHC as primary data source. Second, we use the taxonomy to inductively extract nine purpose-related archetypes, i.e., foundational and distinguishable types (Ross, 1974; van der Valk et al., 2021), of DT. Through a cluster analysis, these purpose-related DT archetypes reflect combinations of DT characteristics typically co-occurring in practice. Finally, we evaluated the reliability, validity, and usefulness of the taxonomy and purpose-related DT archetypes via the Q-sort method, further expert insights (Nahm, Rao, Solis-Galvan, & Ragu-Nathan, 2002) and a longitudinal analysis. Overall, our work contributes to the descriptive knowledge on DT. The resultant taxonomic theory (Gregor, 2006) fosters our understanding of the purposes of DT and lays the ground for further theorizing. Therewith, we also support practitioners to manage and design DTs.

Our paper is structured as follows: In Section 2, we provide background by elaborating on the nature of DT compared to the closely related IT construct and by comparing existing technology classifications. In Section 3, we outline our research design, before introducing the taxonomy and the purpose-related DT archetypes in Section 4 and 5. Thereafter, we present our evaluation results in Section 6 and discuss implications in Section 7. In Section 8, we conclude with a summary and limitations that provide stimuli for future research.

2 Background

As a starting point for developing a purpose-related classification of DTs, we build on the literature from the IS discipline and beyond covering the construct (digital) technology. We start by outlining a brief history of technology and, thereby, also elaborate on the differentiation between the coexisting terms IT and DT. We then draw from the rich body of knowledge on DT to illuminate our understanding of DT and the chosen perspective for this paper (i.e., purpose-related perspective). Thereafter, we compare existing technology classifications in terms of structuring and classifying DT related to their purposes.

2.1 Technology in the Information Systems Discipline

There are many definitions of ‘technology’. Most fundamentally, technologies can be defined as a “collection of devices and methods available to human society” (Arthur & Polak, 2006, p. 23). To refine this fundamental understanding, Arthur (2009) proposed three definitions of technology: (1) as a means to fulfil a human purpose, (2) as an assemblage of practices and purposes, and (3) as the collection of devices and practices available to a culture. Further, he put forward a theory of combinatorial evolution, according to which technology components are miniature technologies themselves, which evolve by constructing new functionality and devices based on existing technology (Arthur & Polak, 2006). Today, technology is a central subject of interest in many disciplines, including, for example, medicine (e.g., Blumenthal, 2011), biotechnology (e.g., Bains, 2003), and IS (e.g., Adomavicius et al., 2008). These disciplines, however, think about and discuss technology differently. More precisely, when Kline (1985) studied the general construct of technology, he uncovered that the understanding of technology depends on its purposes in different contexts. In the IS discipline, technology has always been at the center of research. For example, Davis and Olson (1988) described IS as using “computer hardware and software, manual procedures, management and decision models, and a database” (p. 5) and Klein and Hirschheim (1989, p. 34) stated that “IS and technology can become a force of social progress” (p. 215).

We find two co-existent terms in the IS literature both of which refer to technology but whose distinction is by no means clear: IT and DT. IT is the traditional term which describes technology as a collector, storage, processor, and transmitter of information to automate work (Boaden & Lockett, 1991; Orlikowski, 1992; Silver, Markus, & Beath, 1995; Zuboff, 1989). IT builds on symbol-based computation, i.e., bitstrings that “provide a standard form of symbols to encode input, process, and output of […] tasks” (Benbya, Nan, Tanriverdi, & Yoo, 2020, p. 2). Along these lines, Davis (2000) described IT as the central component of IS, where individuals use IT to “deliver information and communications services for transaction processing/operations and administration/management of an organization” (p. 67). IT characteristics cover a digital and a physical perspective (i.e., soft- and hardware), with the latter becoming manifest in objective forms and functions varying in terms of context and purpose (Orlikowski, 1992). El Sawy (2003) proposed three views of IT, which comply with Porter and Heppelmann’s (2014) waves of IT-driven transformation. First, IT for the purpose of standardization and automation can be seen as a tool separated from individuals and their work. Second, when using IT for the purpose of ubiquitous connectivity, the environment of individuals’ work comprises and integrates IT. Third, when IT becomes an integral part of products and services, it not only fuses into the core of business but also into individuals’ work and personal lives.

As the third wave of IT-driven transformation became increasingly relevant (Porter & Heppelmann, 2014), the scope of IS research broadened and focused on the digital perspective of technology (Baskerville et al., 2020; Kallinikos & Mariátegui, 2011; Tarafdar & Tanriverdi, 2018). As a result, the understanding of IT evolved from Davis’ (2000) traditional perspective to a more holistic one, which led to the emergence of the DT construct. DT is often simply described as an umbrella term for technology in digital contexts (Denner, Püschel, & Röglinger, 2018). More specifically, Bharadwaj et al. (2013) and Vial (2019) describe DT as a combination of information, computing, communication, and connectivity technologies. As DTs are embedded in products and services, they can hardly be disentangled from the underlying IT infrastructure anymore (Henfridsson & Bygstad, 2013; Yoo et al., 2010). DT is known to have pervasive economic and societal effects (Kreuzer et al., 2022; Tim et al., 2021), e.g., as it disperses agency across various actors as well as blurs boundaries between customers and companies as well as products and industries (Oberländer et al., 2021; Yoo et al., 2010). In the IS literature, DT has been predominantly discussed in terms of its nature (e.g., Faulkner and Runde (2019) and Kallinikos et al. (2013)) related phenomena such as digital innovation (e.g., Yoo et al. (2010)) and transformation (e.g., Vial (2019)), and individual technologies such as artificial intelligence (e.g., Ägarfalk (2020)) or digital twins (e.g., van der Valk et al. (2021))

Drawing from this brief historical overview, we find that the DT construct has emerged gradually, making the radical developments in the IS context and beyond tangible. The evolving understanding of technology indicates that the DT construct differs from the traditional understanding of IT, e.g., as proposed by Davis (2000), reaching beyond infrastructure-enabled automation and connectivity. In this regard, owing to DT’s embeddedness in products and services and its immersive role in society, DT is associated with a wider variety of purposes compared to traditional IT. Similar conclusions can be drawn from the large number of DT-related phenomena. While the core of their respective research streams still matches their non-digital counterparts, e.g., digital and (traditional) entrepreneurship (Briel et al., 2021; Kreuzer et al., 2022), the emergence of DT challenged all existing theoretical assumptions, which have been mostly developed when IT was the primary construct in focus. Nevertheless, today, IT and DT still coexist as related constructs, whereby, for example, neither seminal work such as Baskerville et al. (2020), Wessel, Baiyere, Ologeanu-Taddei, Cha, and Blegind Jensen (2021) nor Yoo et al. (2010) proposed a clear distinction between them.

2.2 The Nature of Technology in Digital Contexts

To understand in more detail how IS research conceptualized the nature of DT, we present existing conceptualizations of DT and elaborate on the closely related constructs *digital objects* and *digital artifacts*. Thereafter, we characterize our general understanding of DT in a synopsis that builds on the current state-of-the-art knowledge in the academic literature.

2.2.1 Layered Architecture of Digital Technology

The IS literature follows the idea that DT's embedding in products, services, and individuals' lives is a constitutive property. Thereby, DT has been discussed in terms of architectures (Adomavicius et al., 2008; Gao & Iyer, 2006; Yoo et al., 2010). For example, the Internet architecture includes a content, application, logical, and physical layer (Farrell & Weiser, 2003). In technology ecosystems, i.e., habitats where multiple technologies influence one another, technologies are conceptually split into components, products, or infrastructure (Adomavicius et al., 2008). Investigations on the networked information economy suggest a three-layered understanding of DT with a physical, a logical, and a content layer (Benkler, 2006).

Building on and extending these works, Yoo et al. (2010) proposed the layered modular architecture of DT, which comprises a content, service, network, and device layer. Moreover, Yoo et al. (2010) were the first to define *re-programmability*, *homogenization of data*, and *self-referential nature* as constitutive properties of DTs: Homogenization of data allows for processing digital content, a property that takes a technical perspective where technology converts analog signals into binary numbers in line with symbol-based computing (Rabiner & Gold, 1975). Re-programmability enables the separation of a device's functional logic from its physical embodiment. This leads to the third property, the self-referential nature of DT, which yields positive network externalities (Yoo et al., 2010). As a result of these three properties, a DT embedded in an artifact, e.g., as an outcome of digital innovation, enables convergence, i.e., it can be easily combined with other artifacts, and generativity, i.e., it can be indefinitely extended (Ciriello et al., 2018; Kreuzer et al., 2022; Yoo, Boland, Lyytinen, & Majchrzak, 2012). Yoo et al.'s (2010) conceptualization of DT, i.e., the just introduced three properties enabling convergence and generativity, served as input for many subsequent studies theorizing the nature of DT.

2.2.2 Digital Objects and Digital Artifacts

IS research has built mature knowledge on the constructs digital object and digital artifact, which are both closely related to DT and, thus, not easy to differentiate. Faulkner and Runde (2013, 2019) described digital objects as a combination of material and non-material objects, usually hybrids, whose components include one or more bitstrings. Thus, they are not necessarily completely digital but can also include "[…] relatively small-scale physical devices, ranging from computer systems, components, and peripherals […]" (Faulkner & Runde, 2019, p. 1285). As hybrids, digital objects also inherit the characteristics of their non-material components, i.e., non-rivalry in use, infinite expansibility and re-combinability (Faulkner & Runde, 2011, 2019). Further, digital objects are context-dependent, meaning that a digital object acquires a specific (social) positioning, e.g., functions, rights and responsibilities, within the context of the sociotechnical system in which it is used (Faulkner & Runde, 2019). However, due to the characteristics of a digital object, it can continuously be transfigured, which is why digital objects always signal that they are incomplete and perpetually in the making (Garud, Jain, & Tuertscher, 2009).

To theorize on this phenomenon of constant incompleteness, Kallinikos et al. (2013) deployed the term digital artifacts. In this regard, they argued for and discussed an ambivalent ontology of digital artifacts perceiving them as objects which "lack the plenitude and stability afforded by traditional items and devices" (Kallinikos et al., 2013, pp. 357–358) as they are editable, interactive, reprogrammable, and distributed. Moreover, in line with Faulkner and Runde (2019) argument for the social positioning of digital objects, Ciriello et al. (2019) stated that a digital artifact is always practice-oriented, i.e., its purpose is defined by the practice it is used for. In an effort to untangle some of the overlaps between constructs describing technology in digital contexts, Hund et al. (2021) argued that the presence of a social positioning (Faulkner & Runde, 2019), i.e., purpose, differentiates DT from digital objects. They therefore stated that a “digital object becomes a digital technology when it is assigned a meaning, namely a purpose for applying it, whereby the purpose is determined by social actors such as users” (Hund et al., 2021, p. 5).

2.2.3 Synopsis

Considering these existing conceptualizations of the nature of DT, we make a twofold conclusion for our understanding of DT and the perspective we take for analysing it. First, following studies such as Hund et al. (2021), Ciriello et al. (2019) and Faulkner and Runde (2019), DT is closely linked to the purpose it provides within a social context. This finding also aligns with the way technology in general has always shared associations to its context and purposes, e.g., Kline (1985) and Davis (2000). Hence, we take a purpose-related perspective on DT. In a broader IS context, our research thereby also aligns with the sociomateriality perspective on DT (Orlikowski, 2007, 2010; Orlikowski & Scott, 2015; Scott & Orlikowski, 2014) which assumes inseparability of the social and material (Orlikowski & Scott, 2008). Sociomateriality is based on a relational ontology, whereby, “entities, human beings, and things exist only in relations: they are performed and continuously brought into being through relations” (Cecez-Kecmanovic, Galliers, Henfridsson, Newell, & Vidgen, 2014, p. 809). We argue that purpose is an essential component underlying these relations.

Second, despite the existence of multiple terms for technology in digital contexts, e.g., DT, digital object and digital artifact, there is a clear consensus between studies when conceptualizing the nature of DT: On the one hand, most conceptualizations propose and substantiate a set of properties that render a technology digital. On the other hand, although these sets of properties differ in their level of detail or used terms, they share the idea that DT has a layered modular architecture (Yoo et al., 2010) and enables convergence and generativity (Yoo et al., 2012). Hence, we decided to draw from Yoo et al.’s (2010) DT properties (i.e., re-programmability, homogenization of data, and self-referential nature) as they were one of the first and most fundamental DT conceptualizations, they have been used widely across research streams (Kreuzer et al., 2022) and provide a level of detail sufficient for the purpose of our paper. Moreover, these properties enable differentiating DT from other technology not closely related to IS, e.g., nano- and biotechnology.

2.3 Technology Classifications in Academia and Practice

Classifications have a long history in IS research. They support the description, understanding, and analysis of novel phenomena by classifying objects based on dimensions, characteristics, or attributes (Gregor, 2006; Kundisch et al., 2021; Nickerson et al., 2013). We argue that a purpose-related classification of DTs is highly relevant to research and practice, e.g., to better understand and theorize the diverse purposes of DT or to design DTs serving new purposes. To emphasize the need for such a purpose-related classification and to outline the existing knowledge base, we compare existing technology classifications (see Appendix, Table 5 for details) from academia and practice according to four criteria that are relevant for classifying DT through its purposes: 1) Rigorously developed, 2) applicable to DT, 3) sufficiently concrete to reflect the diverse purposes of DT and 4) sufficiently abstract to be persistent.

A useful DT classification, first, should be rigorously developed and evaluated following transparent research methods and building on theoretical foundation and empirical evidence. Second, a classification should be applicable to DT by considering its nature, i.e., the layered modular architecture, and technology properties enabling convergence and generativity (Yoo et al., 2010; Yoo et al., 2012). Third, a classification should be sufficiently concrete substantiating the diverse purposes of DT to make the assignment to a class meaningful. It therefore needs to provide some descriptions and explanations of the purposes or examples of how related purposes unfold in practice. Fourth, a classification should be sufficiently abstract to be persistent over a reasonably long period of time reaching beyond individual technologies and hence providing a holistic overview of DT purposes. We assessed existing (digital) technology classifications according to these four criteria and present key insights below. A complete overview of the classifications can be found in Appendix A.

While our list may be not exhaustive, to the best of our knowledge, there is no technology classification that addresses all four criteria yet. First, there are classifications provided by the professional literature, which offer tangible yet a-theoretical approaches. For example, describing the 'next set of [digital] technologies', the DARQ acronym includes distributed ledger, artificial intelligence, extended reality, and quantum computing (Accenture, 2019). Consulting and market research agencies also regularly compile technology lists and trend reports, reflecting the growing number and variety of DTs. The GHC, for instance, assigns emerging technologies to early life cycle phases, i.e., *technology trigger, peak of inflated expectations, trough of disillusionment, slope of enlightenment,* and *plateau of productivity*. While these lists and reports provide a valuable and wide overview of emergent technologies, they neither have been developed in a scientifically rigorous manner nor are they persistent. Second, there are technology classifications that do not focus on DT or particularly consider digital characteristics of technology. These studies were often created for similar but not synonymous constructs. For example, Davis (2000) classified IT as infrastructure, repositories, or applications for transaction, processing, operations, administration, or management. Third, other classifications are not sufficiently concrete regarding DT purposes. These studies often define DT simply as a means to investigate DT-related phenomena, for which it is not necessary to fully understand the diverse purposes of DT. For example, the popular SMAC acronym classifies technologies into social, mobile, analytics, and cloud (Evans, 2016; Verma, Kumar, & Sharma, 2016) and, over time, has been extended by Internet of Things (Sebastian, Moloney, Ross, & Fonstadt, 2017; Vashi, Ram, Modi, Verma, & Prakash, 2017) and platforms (Vial, 2019). While these classes provide the potential for further exploration of their corresponding purposes, SMAC has been primarily used to study the phenomenon of digital transformation. Fourth, there are classifications that specifically focus on individual or a sub-set of DTs and are hence not useful to classify all established and emergent technologies, i.e., technologies that have been in use for a long (established) or comparatively short (emergent) period of time (Laycey, Malakar, McCrea, & Moffat, 2019). For example, Power (2004) provided a classification scheme for Decision Support Systems, van der Valk et al. developed a taxonomy and archetypes for digital twins, and Yang and Tate (2012) focused on Cloud Computing.

We conclude that a purpose-related classification of DTs is missing in the IS literature. In our paper, we aim to develop a taxonomic theory that addresses all four criteria. We build on a theoretically well-founded and empirically validated taxonomy of DT (criterion 1), whereby we draw from Yoo et al. (2010) for our understanding of DT to consider digital characteristics of technology (criterion 2). By applying a purpose-related perspective on DT, we will focus on structuring and substantiating purposes of DT (criterion 3). To address criterion 4, we base our work on a diverse sample of DTs that reaches beyond individual or a sub-set of DTs. As Hund et al. (2021, p. 5) made the case that purpose "is determined by social actors such as users", we argue that the purpose of DT is something that can be studied best by analyzing DT close to practice. Therefore, we consider the GHC a sensible primary source for compiling a sample of DTs, enabling us to inductively develop both the taxonomy and purpose-related DT archetypes. Our rationale is that the GHC has been updated annually for two decades and features short definitions per technology. Against this backdrop, it is often used in the academic literature (e.g., O'Leary (2008), Prat (2019) and van der Aalst, Bichler, and Heinzl (2018)). We provide more details on how we compiled our sample of DTs in the following.

3 Research Design

To address our research question, we aimed to build a taxonomic theory (Gregor, 2006) for DT that enables the classification and understanding of its purposes. McKelvey (1982) argued that systematics such as classifications are a necessary first step to develop sound scientific methods (Gregor, 2006). To systematically identify relevant classes of a phenomenon of interest, i.e., DT in our paper, researchers must first conceptualize potential characteristics to determine similarities and differences of real-world objects. To do so, McKelvey (1982) suggested to use taxonomies which, today, are a proven and well-established research outcome in the IS discipline (Gregor, 2006; Kundisch et al., 2021). IS literature thereby often uses taxonomies to derive archetypes (Kundisch et al., 2021), i.e., foundational and distinguishable types or classes underlying the phenomenon or objects of interest (Ross, 1974; van der Valk et al., 2021).

For the research design of our paper, we decided to follow McKelvey's (1982) 'organizational systematics' paradigm as it covers the most essential steps to build a sound classification and to operationalize it through 'state of the art' classification methods from the IS literature. More precisely, we adopted Nickerson et al.'s (2013) taxonomy development approach to develop a multi-layer taxonomy for individual

DTs and applied cluster analysis (Strauss & Maltitz, 2017; Ward, 1963) to inductively extract purpose-related DT archetypes. Below, we first present our strategy for compiling a sample of DTs as the empirical basis for our iterative taxonomy development. Thereafter, we describe our taxonomy development process before outlining important decisions of the cluster analysis. Finally, we present our evaluation approach.

3.1 Compiling a Sample of Digital Technologies

To develop and evaluate both the taxonomy and the purpose-related DT archetypes, we compiled a sample of DTs. To study DT close to practice (Hund et al., 2021) and account for the fast development of DTs, we therefore mainly used technology reports offered by consultancies and market research institutes as sources (Table 1).

Table 1. Technology Reports used for Compiling a Sample of Digital Technologies

Publisher	Details on publisher	Title of issue	DTs per Issue	First appearance	Publication frequency	Technology domain
Accenture	Management consulting	Technology Vision	5	2015	annual	digital / social
Deloitte	Auditing and consulting	Deloitte Tech Trends	8	2014	annual	digital / social
Forbes	Business magazine	Top 10 Trends for Digital Transformation	10	2017	annual	digital
Forrester	Market research institute	Top Technology Trends To Watch	10	2012	triennial	digital
Future Today Institute	Management consulting	Tech Trends Annual Report	159 - 225	2017	annual	mixed *
Gartner	Market research institute	Gartner Hype Cycle for Emerging Technologies	19-47	2000	annual	digital
MIT Technology Review	Technology magazine	10 Breakthrough Technologies	10	2001	annual	mixed *
Scientific America	Popular science magazine	Top 10 Emerging Technologies	10	2015	annual	mixed *
World Economic Forum	Economic (non-profit) foundation	Top 10 Emerging Technologies	10	2012	annual	mixed *
*Note: Mixed: comprises, inter alia, bio, nano, neuro, and energy technologies						

After comparing the available technology reports, we found that the majority either describes DTs on a high level of abstraction or includes technologies from different disciplines such as medicine, biology, sociology, or energy. As already justified in the background, the GHC fits our purposes best as it mainly focuses on emergent technologies in the digital context. Moreover, the GHC is the only source that enables a long-term view on technology development, as it has been published continually for two decades. Hence, we used the GHC as our primary source and initially identified 140 technologies from the years 2009 to 2017. We chose this timeframe to have both prior and later editions of the GHC left for the evaluation. Appendix B lists all 140 technologies included in the GHC from 2009 to 2017. To offset potential bias, we drew on the other technology trends from Table 1 for cross-checking purposes.

To ensure that the DTs included in our sample were comparable regarding their level of abstraction and digital in nature, we developed the following assessment criteria. As a prerequisite, we required each DT to be different from any other DT to ensure that each could be judged based on its unique definition. Where this was not the case, we merged the respective DTs, which shared one definition and did not appear within the same GHC edition. We also reduced the sample in accordance with formal and content-oriented requirements. First, the definition of a DT included in the GHC had to provide sufficient information for classification. Second, the DTs had to be on a similar level of abstraction – as far as could be subjectively judged. Third, each DT had to comply with Yoo et al.'s (2010) DT properties.

After analyzing the 140 initially identified DTs against the assessment criteria, we obtained a sample of 92 DTs for the years 2009 to 2017 (Appendix B). With regards to the validity of our sample, we could map three quarters of these DTs to at least one additional technology report from Table 1. Conversely, we did not find any DTs in the other technology reports which were not included in the respective GHCs. Hence, we are confident that our sample is comprehensive and fits our purpose of developing and validating a multi-layer taxonomy and purpose-related DT archetypes.

3.2 Developing a Taxonomy for Digital Technologies

Taxonomy development has been successfully applied in various IS contexts (Kundisch et al., 2021; Lösser, Oberländer, & Rau, 2019). Taxonomies are classification schemes unfolding characteristics and dimensions of a phenomenon. Thus, they can be used to group objects on the basis of similarities and differences (Nickerson et al., 2013) and to derive archetypes (e.g., van der Valk et al. (2021)). In line with McKelvey (1982), we aimed to develop a taxonomy as a first artifact of our taxonomic theory (Gregor, 2006).

We applied Nickerson et al.'s (2013) iterative taxonomy development approach, as it incorporates "methodological recommendations for taxonomy development from other disciplines" (Lösser et al., 2019, p. 3). In IS research, Nickerson et al. (2013) were the first to provide a systematic, transparent, and replicable taxonomy development method (Lösser et al., 2019). Initially, this method demands for the determination of a so-called meta-characteristic, representing the main purpose of the taxonomy. Subsequently, it requires determining objective and subjective ending conditions. With this, the prerequisites are set to choose an approach per iteration, i.e., conceptual-to-empirical or empirical-to conceptual. The conceptual-to-empirical approach conceptualizes dimensions and characteristics deductively, primarily derived from the literature and complemented by the researchers' creativity and justificatory knowledge. After assigning real-world objects – in our paper: DTs from our sample – to the dimensions and characteristics, an initial or revised taxonomy is obtained. The empirical-to-conceptual approach first identifies objects, which are then grouped and dimensions as well as characteristics are developed inductively. After each iteration, the ending conditions must be checked. The taxonomy development process continues until all ending conditions are met.

Our instantiation of the taxonomy development process comprised five iterations. As the field of DTs is fast-moving, we applied both approaches – starting with a conceptual-to-empirical iteration to account for extant knowledge followed by four empirical-to-conceptual iterations to account for characteristics of the DTs from our sample. We began the taxonomy development process by defining the meta-characteristic. In line with our idea of using the taxonomy as a means for classifying individual DTs and for developing purpose-related DT archetypes, we chose *'characteristics of individual DTs'*. As recommended by Nickerson et al. (2013), we used the following objective ending conditions: (1) each characteristic is unique within its dimension, (2) each dimension is unique and not repeated within the taxonomy, (3) at least one object must be identified per characteristic and dimension, and (4) an iteration does not imply further modification of the taxonomy. We also chose subjective ending conditions, which are met if the taxonomy is concise, robust, comprehensive, extendible, and explanatory based on the co-authors' assessment (Nickerson et al., 2013). Table 2 provides an overview of the taxonomy development process, including the approach per iteration, the number of classified objects, and the ending conditions. Appendix C provides details for every iteration, including methodological design decisions.

3.3 Developing Purpose-related Digital Technology Archetypes

Following McKelvey (1982), identifying purpose-related DT archetypes requires understanding which combinations of DT characteristics typically co-occur in reality and which purpose they acquire as part of the DT's social positioning (Faulkner & Runde, 2019; Hund et al., 2021). Hence, we classified the individual DTs from our sample using the taxonomy, applied cluster analysis to inductively develop DT archetypes, identified purpose-related names and further substantiated each archetype.

Cluster analysis is a statistical technique that groups similar objects (Field, 2013; Hair, Black, Babin, & Anderson, 2010), aiming for homogeneity within and heterogeneity among clusters (Cormack, 1971). We used Ward's (1963) agglomerative hierarchical clustering algorithm, as it has been often applied (Ferreira & Hitchcock, 2009; Saraçli, Doğan, & Doğan, 2013), achieved good results in comparable studies, determines the entire cluster hierarchy, and provides comprehensible cluster solutions (Montani & Leonardi, 2014; Weerdt, van den Broucke, Vanthienen, & Baesens, 2013). As opposed to partitioning algorithms, which use a predetermined number of clusters, hierarchical algorithms merge or divide clusters to create solutions for all possible numbers of clusters (Vendramin, Campello, & Hruschka, 2010). As a distance measure, we chose the Manhattan-metric that has proven useful in combination with the Ward algorithm (Strauss & Maltitz, 2017). Details on the encoding are included in Appendix D.

Table 2. Details on the Iterative Taxonomy Development Process

Iteration	Approach *	Real-life Objects	Total number of Layers / Dimensions / Characteristics	**Major Changes**	**Ending Conditions** *(selection, not exhaustive)*
1	C2E	Several technologies from multiple sources (cf. Table 1)	6 / 10 / 34	Superset of layers, dimensions, and characteristics as a starting point for subsequent iterations.	Subjective and objective ending conditions not met: - not at least one identified real-life object for certain characteristics. - not concise due to a large number of dimensions and characteristics.
2	E2C	46 DTs from the GHCs of 2015 to 2017 classified by co-authors	6 / 11 / 37	Addition of one dimension and associated characteristics. Modification of multiple characteristics.	Subjective ending conditions not met: - not concise due to a large number of layers, dimensions, and characteristics. - not comprehensive as not all real-life objects could be classified.
3	E2C	10 DTs from the GHCs of 2015 to 2017 classified by two different focus groups	4 / 8 / 23	Abandonment of two layers and three dimensions. Condensing of some characteristics.	Subjective ending conditions not met: - not explanatory, as focus group members could not clearly classify the sample without complete information on the respective real-life object. - not concise due to a large number of dimensions and characteristics.
4	E2C	92 DTs from the GHCs of 2009 to 2017 classified by co-authors	4 / 8 / 20	Replacement of one dimension and associated characteristics due to significant overlap with other dimensions.	Objective ending conditions not met: - extension of the sample resulted in adding and deleting characteristics, which required a modification of the taxonomy.
5	E2C	92 DTs from the GHCs of 2009 to 2017 classified by co-authors	4 / 8 / 20	No further modification to the taxonomy.	All objective and subjective ending conditions are met: - each characteristic is unique within its dimension. - each dimension is unique and not repeated. - at least one object has been identified per dimension and characteristic. - the iteration does not imply further modifications. - all co-authors agree that the taxonomy is concise, robust, comprehensive, extendible, and explanatory.
*Note: C2E: Conceptual-to-Empirical; E2C: Empirical-to-Conceptual					

Regarding the ideal number of clusters, the literature offers various measures, however, there is no agreement as to which is the best (Wu, 2012). To address this ambiguity and leverage the advantages of the different measures, we calculated 16 common clustering validation indices (see Appendix D for details), e.g., Ball and Hall (1965), Beale (1969) and Duda and Hart (1973). In accordance with our data set and the Ward algorithm, we calculated clustering validation indices for hard (i.e., every object is part of exactly one cluster) and internal (i.e., information is only used if it is also needed to conduct the cluster analysis) clustering. The recommended number of clusters ranged from 2 to 15, with a tendency towards 9 clusters represented by one quarter of the indices. Noticing that some indices tended to seek the cluster solution at the limits of the range, we narrowed our search by neglecting such indices. We then discussed all cluster solutions for the remaining indices, which ranged from 5 (Hartigan, 1975) to 13 (Davies & Bouldin, 1979). Thereby, we focused on the interpretability of individual clusters with regards to their purposes, while keeping the trade-off between homogeneity per cluster and the manageability of the overall solution in mind (Milligan & Cooper, 1985; Sneath & Sokal, 1973). In the end, we chose the cluster solution covering nine DT archetypes referring to nine clearly distinguishable and comprehensible purposes.

At last, in line with our purpose-related perspective, we aimed to identify purpose-related names and substantiate the purposes for all archetypes. Purpose-related naming means that the name of each DT archetype can be read as “DTs for [*specific purpose*]”. To identify an initial set of names, we decided to build on the knowledge we acquired in the author team throughout the entire research process. We examined the most frequent taxonomy characteristics per cluster in detail and reflected on the resulting purposes of the individual DTs within the cluster. All authors then suggested names independently, which we consolidated and discussed iteratively in several author workshops. Once we had agreed on an initial set of names, we drew from justificatory knowledge in the IS literature to validate the names and substantiate each archetype. Most importantly, for each archetype, we identified key characteristics, outlined illustrative examples of assigned DTs (Kundisch et al., 2021), and highlighted connected IS research areas. Moreover, during the evaluation (see Section 3.4), we continuously challenged and refined the archetypes’ names and substantiations based on a Q-sort within the author team as well as with practitioners.

3.4 Evaluation

To evaluate our taxonomic theory regarding the criteria reliability, validity, and usefulness, we followed, on the one hand, established taxonomy evaluation practices in general as outlined by Szopinski, Schoormann, and Kundisch (2019) and Kundisch et al. (2021) as well as specific evaluation strategies of articles that have been published in well regarded IS journals or conferences (e.g., Senior Scholars’ Basket of Journals), such as Püschel, Röglinger, and Schlott (2016), Oberländer, Kees, Röglinger, and Rosemann (2018), and Oberländer et al. (2021). More specifically, we (1) assessed the taxonomy’s reliability through independently classifying DTs according to dimensions and characteristics, (2) applied the Q-sort method to assess the DT archetypes (Table 3), both internally and externally, (3) asked for qualitative expert assessment, and (4) conducted a longitudinal analysis of GHC DTs from 2000 to 2020.

First, having completed the taxonomy development process, we determined the taxonomy’s reliability via dimension- and object-specific hit ratios and prepared additional descriptive statistics to validate its applicability. Hit ratios measure co-authors’ agreement regarding the classification of our sample (Nahm et al., 2002), whereby the assigned values range from 1 for complete agreement to 0 for complete disagreement. To ensure comparability among exclusive dimensions (i.e., characteristics are mutually exclusive) and non-exclusive dimensions (i.e., characteristics are not mutually exclusive), we determined absolute and relative hit ratios. Absolute ratios capture the relation between the number of observations per characteristic and the total number of objects. For non-exclusive dimensions, we further calculated the relative ratio, which relates the number of observations per characteristic and the total number of observations per dimension.

Second, used to test taxonomies and related clusters (Carter, Kaufmann, & Michel, 2007; Püschel, Roglinger, & Brandt, 2020; Rajesh, Pugazhendhi, & Ganesh, 2011), the Q-sort method is a statistical tool that examines peoples’ attitudes and opinions (Stephenson, 1935). Two or more judges (P-set) with a clear understanding of the topic (Carter et al., 2007) classify a set of objects (Q-set) to predefined constructs to evaluate the degree of their joint understanding. For the *internal Q-sort*, two co-authors who were not yet familiar with the cluster results mapped the DTs to the inferred archetypes. We measured reliability using Cohen’s Kappa (Cohen, 1960), defined as the proportion of joint judgment in which there is agreement after chance agreement is excluded (Nahm et al., 2002). Considering the frequency of correctly assigned objects, validity is measured through object-specific and overall hit ratios (Moore &

Benbasat, 1991). For the *external Q-sort*, we consulted twelve experts from industry via an online questionnaire. After a brief introduction of the DT archetypes, the experts classified 18 selected DTs, whereby this sample included two DTs per archetypes. All experts were technology savvy and either held a strategic position within their organization (e.g., CFO), were directly involved in digitalization (e.g., Head of IT), or both (e.g., CIO). Here, we used the Fleiss' Kappa (Fleiss, 1971), as we had more than two judges.

Table 3. Evaluation Criteria for the Internal and External Q-Sort

	Internal Q-Sort	External Q-Sort
Judges (P-set)	Two co-authors, not familiar with the DTs	Twelve experts from industry, holding a strategic position or being involved with IT topics
Sample (Q-set)	92 DTs from the GHCs of 2009 to 2017	18 DTs from the GHCs of 2009 to 2017
Construct validity measure	Hit ratio(s) (Moore & Benbasat, 1991)	Hit ratio(s) (Moore & Benbasat, 1991)
Reliability measure	Cohen's Kappa Coefficient (Cohen, 1960)	Fleiss' Kappa Coefficient (Fleiss, 1971)

Third, we asked the experts to assess the perceived usefulness of the taxonomy and archetypes through the same online questionnaire that we used for the external Q-sort. We thereby invited them not only to share their general thoughts with us but also to outline concrete use cases in which they could see applicability of the archetypes.

Fourth, in line with the organizational systematics paradigm (McKelvey, 1982; Ross, 1974), we complemented the Q-sort by challenging the archetypes' robustness over time by examining their year-wise occurrence in the GHC, i.e., a longitudinal analysis.

In Section 4 and Section 5 we present the final versions of the taxonomy and archetypes, i.e., after all changes resulting from the evaluation have been incorporated. In Section 6, we elaborate on the key results of the evaluation by discussing the evaluation criteria, outlining findings from the Q-Sort and by presenting interesting insights from the longitudinal analysis.

4 Taxonomy of Digital Technologies

4.1 Overview

We now present the taxonomy of DTs including layers, dimensions, and characteristics (Figure 1), accompanied by examples. The taxonomy takes the perspective of individual DTs. To enhance the structure of our taxonomy, we identified layers for grouping dimensions. During the taxonomy development, it become apparent that the identified dimensions fit Yoo et al.'s (2010) layered DT architecture. Hence, we grouped the dimensions according to the layers *device*, *network*, *content,* and *service*.

Starting from a technical perspective, the *device* layer accounts for devices that allow DTs to perform their functions. Broadening the focus on physical devices (Benkler, 2006) through the inclusion of logical capabilities, Yoo et al. (2010) divide this layer into physical machinery and logical capabilities. Our taxonomy accounts for this distinction by including the role of technology and its scope regarding the physical and the digital world as dimensions. To describe the socio-technical interactions of DTs, we included the *network* layer. Yoo et al. (2010) characterize networks as structures of physical transport and logical transmission. For our purposes, the taxonomy includes the direction of information flow and the number of entities involved as dimensions. The *content* layer refers to the key resource of DTs, i.e., received and provided data, and it specifies how data is processed. Finally, the *service* layer addresses the usage of DTs by referring to their functionality (Arthur, 2009) and thereby differentiates between the extents of human involvement. Below, we provide details on all dimensions and characteristics.

Layer	Dimension	Characteristic					Exclusivity[1]
Device	Role of Technology	Application		Infrastructure			ME
	Scope	Cyber		Cyber-Physical			ME
Network	Multiplicity	One-to-One	One-to-Many		Many-to-Many		ME
	Direction	Uni-directional		Bi-directional			ME
Content	Data Treatment	Collection	Aggregation	Analysis	Execution	Transmission	NE
	Input	Digital		Physical			NE
	Output	Digital		Physical			NE
Service	Human Involvement	Active Usage		Passive Usage			ME

Figure 1. Multi-layer Taxonomy of Digital Technology

4.2 Device Layer

The *role of technology* addresses a DT's function either stand-alone or in enabling the application of other DTs. According to Adomavicius, Bockstedt, Gupta, and Kauffman (2004), the role of a technology is essential for understanding its functionality. Every DT is bound to devices, which may represent its core or the underlying hardware as well as software not necessarily tied to a specific predefined infrastructure. In our context, 'application' technologies (e.g., Machine Learning or Smart Advisory) provide sets of functions that directly address and satisfy user needs. 'Infrastructure' technologies (e.g., Neuromorphic Hardware or Hybrid Cloud Computing), by contrast, build the foundations for applications and add value by supporting, enabling, and enhancing functionality. Unlike Adomavicius et al. (2004), we do not include a 'component' characteristic as it did not comply with our subjective ending conditions. According to Arthur's (2009) idea of combinatorial evolution, 'components' (i.e., technological subunits) are aggregated into higher-level technologies. As stand-alone technologies may become components or exist in both forms, the definition of a 'component' leaves room for interpretation and depends on the point in time at which the taxonomy classification took place.

The *scope* dimension addresses a DT's range of actions in line with major contributions on cyber-physical systems (Kagermann, Wahlster, & Helbig, 2013; Zamfirescu, Pirvu, Gorecky, & Chakravarthy, 2014). Our taxonomy distinguishes between a 'cyber' and 'cyber-physical' characteristic. The 'cyber' scope refers to DTs only located within the digital world. This applies to platforms, networks, or analytical technologies without human machine interfaces (HMI) as well as to DTs such as Quantum Computing (Horvath & Gerritsen, 2012). A 'cyber-physical' focus is characterized by a DT's additional connection with and influence on the physical environment. Virtual Reality, for instance, changes the way a human perceives its physical environment.

4.3 Network Layer

The *multiplicity* dimension addresses a DT's socio-technical interaction capabilities. Also referred to as transmission or connectivity (Borgia, 2014), a network captures information exchange among the entities involved (Bucherer & Uckelmann, 2011). Referring to a network as an arrangement of nodes and edges, *multiplicity* provides information about the number and order of nodes involved. Broadening the entity definitions for human-computer interaction developed by Porter and Heppelmann (2014), we distinguish three human-technology or technology-technology interaction types. In 'one-to-one' interactions, the number of participants is limited to two, although an entity is not necessarily an individual, but may be a group of similar entities. This applies to many DTs with interfaces to the physical world, such as Augmented and Virtual Reality. 'One-to-many' interactions implement the idea of hubs, building a central system connecting several entities simultaneously (e.g., Hybrid Cloud Computing). Most complex is the 'many-to-many' interaction form, where the underlying technology connects all participating entities. Notable examples are wireless networks like 802.11ax or next-generation cellular standards such as 5G, which support devices' fast transmission rates.

[1] ME = Mutually exclusive; NE = Non-exclusive

The *direction* dimension covers how DTs exchange data. Again, referring to a network as an arrangement of nodes and edges, the direction characterizes the edges between the nodes involved. Similar to a one-way-street, ‘uni-directional’ communication limits the exchange of data to one direction. Examples include sensor technologies, which solely generate and forward data (e.g., Smart Dust), but also DTs that receive and process data without sending data in return (e.g., 3D Printers). In contrast, ‘bi-directional’ flows allow data to be exchanged in more than one way as the sequence and direction of the data flow is not predetermined. This applies, for example, to DTs with HMIs, which freely communicate and interact with its users (e.g., Natural Language Question Answering).

4.4 Content Layer

The *data treatment* dimension addresses how DTs process data. Püschel et al. (2020) differentiate between transactional or analytical usage, whereas Miller and Mork (2013) introduce three modes of data interaction, i.e., (1) data discovery, subsuming the activities of collecting, inventorying, and preparing data, (2) data integration, referring to the activity of combining disparate data, and (3) data exploitation, referring to analytics which allow for the generation of insights. From an IoT perspective, Borgia (2014) proposed similar categories by differentiating three consecutive phases of collection, transmission and process, and management and utilization. On this foundation, our taxonomy includes five types of data treatment: Data ‘collection’ refers to the generation of data and includes the accumulation of data from different sources (e.g., Smart Dust). Data ‘aggregation’ stores, manages, aggregates, and/or integrates formerly unstructured data (e.g., Enterprise Taxonomy and Ontology Management). Data ‘analysis’ provides techniques to assemble, exploit, and interpret data (e.g., Smart Advisors). Data ‘execution’ refers to transactional usage, characterizing DTs that are triggered on the basis of instructions and thus execute commands (e.g., 3D Printing). Lastly, Data ‘transmission’ focuses on the exchange of data among entities involved (e.g., Wi Fi networks like 802.11ax). As most emerging DTs handle data in more than one specific way, the characteristics of this dimension are non-exclusive.

The *input* and *output* dimensions address how DTs receive and provide data. As every interaction or operation involves the exchange of data, we consider DTs to have data input and output, whereas the respective type of data can assume different states. Depending on the DT at hand, this characteristic is either ‘digital’ (also including non-digital forms of computing such as Quantum Computing) or ‘physical’ (signals perceptible with sensory organs, e.g., visual, acoustic, or haptic). Virtual Reality, for example, transforms digital input into a physically perceptible 3D environment, surrounding its user. Smart Dust, by contrast, scans the physical environment and generates digital data for further purposes. As combinations of characteristics could be observed in our sample, both dimensions are non-exclusive.

4.5 Service Layer

Finally, the *human involvement* dimension addresses how a DT is used by humans. We decided to add this dimension after feedback from focus group meetings to emphasize the role of humans and to account for the trend towards HMI-supported DTs. Thereby, we follow Arthur (2009) who discussed technology usage by and its purpose for humans. ‘Active usage’ means that humans directly use DTs (e.g., Wearables). ‘Passive usage’, by contrast, means that humans are not in direct contact with a DT. For example, this is the case for network structures or hardware, such as 802.11ax and Neuromorphic Hardware.

5 Purpose-related Digital Technology Archetypes

The cluster analysis, which we performed on our sample classified according to the taxonomy, resulted in nine purpose-related DT archetypes. Each archetype reflects a combination of DT characteristics typically co-occurring in reality (Figure 2). Appendix E provides classification details for each DT. Importantly, the DT archetypes were developed inductively based on data from nine subsequent years. Providing an additional overarching structure that supports intuitive classification, we found that the DT archetypes can be further categorized into *infrastructure* technologies and *application* technologies. *Application* technologies can be further divided into *bridging*, *intelligence*, and *interaction* technologies. Below, we provide details per DT archetype including their *purpose*, *key characteristics,* and *examples*. As for the examples, the presented descriptions are taken almost literally from the GHC. For each archetype, we included at least two examples to illustrate that each covers a certain range of DTs and elaborate on how the DT archetypes connect to the literature. To that end, we draw from selected IS publications. At last, we provide an overview of the unique combinations of characteristics for each archetype to increase transparency regarding the assignment process of DTs to archetypes.

Infrastructure technologies enable efficient data and information sharing among various parties involved. Thereby, they provide the (cyber-) physical foundation that *application* technologies need to build on. *Infrastructure* technologies include *connectivity & computation, platform provision,* and *personal mobile communication* technologies.

Connectivity & computation includes DTs with the *purpose* of efficient data processing or exchange, which are mainly *characterized* as 'infrastructure' and by 'passive usage'. Geared towards data 'transmission', this DT archetype processes 'digital' input and output in 'many-to-many' interactions and 'bi-directional' data flows. Invisible for users, related DTs act in the 'cyber' world. As an *example*, 802.11ax not only raises the data throughput of single Wi-Fi devices, but also supports a larger number of simultaneously connected devices (Gartner Inc., 2016). Another example is Quantum Computing, a technology based on the quantum state of subatomic particles representing information denoted in single elements known as quantum bits (Gartner Inc., 2016). As illustrated in the background, this DT archetype is closely related to the traditional understanding of IT as part of the infrastructure. According to Silver et al. (1995), the basic part of IT infrastructure includes computer and communication network components, operating systems, and utilities enabling the usage of independent or shared applications. In the recent IS literature, connectivity and computation are discussed in a broader context, e.g., as the foundation for system interaction through which distributed work is coordinated and executed (Alter, 2018) or in terms of digitally connected enterprises where connectivity facilitates collaboration and information sharing (Levermore, Babin, & Hsu, 2010). Finally, this DT archetype resembles Bharadwaj et al.'s (2013) idea of computing and connectivity technologies.

Platform provision comprises DTs that serve the *purpose* of providing unified access to data or digital services. 'Actively used', platforms are *characterized* as 'infrastructure' as well as by the 'transmission' of 'digital' input and output. As hubs, platforms differ from other network structures in terms of their 'one-to-many' multiplicity, connecting entities in a 'bi-directional' manner. Just like the *connectivity & computation* archetype, platforms only act in the 'cyber' world. For *example*, (Mobile) Application Stores are cloud-based or deployed on premise, providing users with the ability to search for and download applications via a central storefront client (Gartner Inc., 2012). Underlining the infrastructural character, the example of general Cloud/Web Platforms describes the provision of access to different web functionalities, including capabilities enabled not only by technology, but also by community and business aspects (Gartner Inc., 2011). IT platforms are broadly defined as a general-purpose technology, enabling various applications and opportunities (Fichman, 2004). Apart from computing platforms, which are one of the key constituents of IT infrastructure (Benitez, Ray, & Henseler, 2018), the IS literature describes infrastructure platforms, software development platforms, and application platforms (Fichman, 2004). Finally, this DT archetype addresses the ideas of data availability and distribution (Bharadwaj et al., 2013; Loebbecke, 2006) and the 'cloud' component of SMAC (Dewan & Jena, 2014; Evans, 2016).

Personal mobile communication covers DTs that serve the *purpose* of enabling personal, location-independent access to and use of digital data through portable hardware components. This DT archetype is mainly *characterized* by its role of a tangible 'infrastructure' and 'active usage'. It includes individual mobile devices, which also allow for data 'collection' and 'transmission' with 'physical' input and output, enabling 'one-to-one' and 'bi-directional' interactions with users. Differing from *connectivity & computation* and *platform provision*, this DT archetype has a 'cyber-physical' scope. As an *example*, E-Book Readers enable purchasing and consuming digital media such as books or newspapers. Before users can exploit their full functionality, mobile devices must be connected to a platform/marketplace. As this access is either offered via wireless connection or by linkage to a PC, E-Book Readers serve as intermediary between users and platforms/marketplaces (Gartner Inc., 2011). A similar example are Media Tablets, devices based on a touchscreen display that facilitates content entry via an on-screen keyboard (Gartner Inc., 2012). Overall, this DT archetype is reminiscent of the so-called mediated-action perspective, describing technology as a mediational means (Kaptelinin & Nardi, 2012). It also resembles the 'mobile' component of the SMAC classification (Dewan & Jena, 2014; Evans, 2016) and is closely related to Fitzgerald, Kruschwitz, Bonnet, and Welch's (2014) idea of mobile and embedded devices.

In contrast to *infrastructure* technologies, *application* technologies directly engage with end-users to be applied in various contexts for various purposes. Specifically, we found three overarching types of *application* technologies with the aims of *bridging* the virtual and the digital world, providing *intelligence* through analytical or cognitive features, and facilitating novel forms of *interaction*. To start with, *bridging* technologies, i.e., *sensor-based data collection* and *actor-based data execution,* transform digital input into physical output, or vice versa, thereby bridging the gap between the virtual and the physical world.

Sensor-based data collection encompasses DTs that serve the *purpose* of collecting real-world data and their transformation into digital data. Related DTs are 'actively used' for 'collecting' data and further *characterized* by 'physical' input and 'digital' output in 'one-to-one' and 'uni-directional' interactions. Taking the role of an 'application', this DT archetype has a 'cyber-physical' focus. As an *example*, Gesture Recognition uses sensors or cameras to track the motion of users. Advanced approaches (e.g., gaming controllers) even distinguish different types of hand movements such as squeezing, swiping, or pinching (Gartner Inc., 2011). Smart Dust, in turn, refers to dust particles as tiny wireless systems that can detect light, temperature, pressure, or vibration. They run on a wireless computer network and are distributed over an area to perform (sensing) tasks (Gartner Inc., 2017). While sensors have existed for more than a century, modern sensors with integrated information and communication technology capabilities (i.e., smart sensors) made remarkable progress in storage, energy management, or connectivity, playing a key role in industrial and private applications (McGrath & Scanaill, 2014). In the context of cyber-physical systems (Kagermann et al., 2013), sensors observe changes in the physical environment and transform data into signals for further processing (Akyildiz & Kasimoglu, 2004), enabling highly adaptive and self-organizing systems (Broy, Cengarle, & Geisberger, 2012; Yoon, Shin, & Suh, 2012). Another important research area is the field of wireless sensor networks (e.g., in terms of IoT), where the application of sensors includes, for example, environmental, industrial, and traffic monitoring (Xu, He, & Li, 2014).

Actor-based data execution covers DTs that serve the *purpose* of transforming digital data into physical actions or artifacts. As the counterpart of *sensor-based data collection*, this DT archetype is *characterized* by 'active usage' but stands out from all other archetype in terms of data 'execution'. Accordingly, related DTs transform 'digital' input to 'physical' output in 'one-to-one' and 'uni-directional' interactions. Taking the role of an 'application', this DT archetype has 'cyber-physical' focus. An *example* is 3D Printing, which creates three-dimensional objects by converting digital models into physical shapes using different materials and solidifying processes (Gartner Inc., 2012). Moreover, the next generation of 4D Printing describes a technique where the materials are additionally encoded with a dynamic capability – either function, confirmation, or properties – that can change via the application of chemicals, electronics, particulates, or nanomaterials (Gartner Inc., 2017). Accordingly, Kagermann et al. (2013) describes actors as a another fundamental component of cyber-physical systems, where they translate control signals into physical actuation (Akanmu, Anumba, & Messner, 2012; Nof, 2009).

Intelligence technologies, i.e., *analytical insight generation* and *self-dependent material agency,* provide advanced analytical or cognitive features.

Analytical insight generation covers DTs that serve the *purpose* of analyzing digital data to support knowledge creation and decision-making. Accordingly, this DT archetype is *characterized* by 'active usage' and data 'analysis', which processes 'digital' input and output in 'bi-directional' 'one-to-one' interactions. Related DTs serve as 'applications' exclusively acting with a 'cyber' scope. As an *example*, In-memory Analytics enable fast query and calculation tasks against large volumes of data by loading detailed data into memory (Gartner Inc., 2014). Another example is Machine Learning, a technology that aims to extract certain kinds of knowledge, i.e., patterns, from a series of observations (Gartner Inc., 2017). This DT archetype is well-aligned with recent IS literature investigating the potential of big data analytics (Sharma, Mithas, & Kankanhalli, 2014). Spurred by increasing data availability, advanced algorithms, and computing power (Seddon, Constantinidis, Tamm, & Dod, 2017), big data analytics is described by scholars in different contexts. Among others, this includes the process of extracting useful knowledge in the context of data mining (Witten, Frank, Hall, & Pal, 2017), data warehousing (Watson, Goodhue, & Wixom, 2002), data-driven business processes, or decision making (Lycett, 2013). Finally, this DT archetype resembles the 'analytics' component of SMAC (Evans, 2016), the 'artificial intelligence' component of DARQ (Accenture, 2019), as well as Fitzgerald et al.'s (2014) distinction of 'analytics' against social media, mobile technologies, and embedded devices.

Self-dependent material agency covers DTs that serve the *purpose* of collecting and analyzing both digital and physical data to enable self-dependent action in the physical world. Just like *analytical insight generation*, this DT archetype is *characterized* by 'active usage' and data 'analysis', which is extended by further developed data treatment capabilities of 'collection', 'analysis', 'execution' and 'transmission'. This DT archetype processes 'digital' and 'physical' input and output within 'bi-directional' 'one-to-many' interactions. Taking the role of an 'application', this DT archetype acts with a 'cyber-physical' focus. As an *example*, Autonomous Vehicles are capable of making decisions moving to a predetermined destination without human intervention. To do so, they use positioning and sensing technologies such as radar or cameras to perceive their environment (Gartner Inc., 2017). This DT archetype relates to recent academic discussions on smart things and the IoT, which are expected to become autonomous actors in digital value networks (Oberländer et al., 2018). Smartness relies on data availability, combination, and advanced analysis for diagnostic, predictive, and prescriptive purposes (Porter & Heppelmann, 2014; Want, Schilit, & Jenson, 2015). Advanced data analysis also serves as foundation for self-x capabilities (e.g., self-configuration, -optimization, -diagnosis, or -healing), which in turn enable autonomous operations and the material agency of DTs (Beverungen, Müller, Matzner, Mendling, & vom Brocke, 2019).

Finally, *interaction* technologies, i.e., *augmented interaction* and *natural interaction,* facilitate novel forms of communication and interaction with humans.

Augmented interaction relates to DTs that serve the *purpose* of analyzing digital data and presenting them in a physical form to support humans in their tasks. Accordingly, this DT archetype is *characterized* by 'active usage' and data 'transmission', which processes 'digital' input to 'physical' output within 'one-to-one' 'bi-directional' interactions. Related DTs serve as 'applications' and act with a 'cyber-physical' scope. As an *example*, Augmented Data Discovery enables users to automatically find, visualize, and narrate relevant findings, such as correlations, exceptions, clusters, and predictions, without having to build models or algorithms. Users explore data via visualizations, supported by natural-language generated narration and interpretation of results (Gartner Inc., 2017). Virtual Personal Assistants, in turn, support users by predicting their needs via the observation and analysis of behavior. When required, these DTs act autonomously on the users' behalf, e.g., prioritizing e-mails by content and urgency, and performing associated tasks (Gartner Inc., 2016). This DT archetype refers to the extended or mixed 'reality' technology listed within the DARQ acronym. It describes virtual and augmented reality technologies which transform interactions in the professional and private environment by assisting humans through information provision and decision support (Accenture, 2019). With this, digital artifacts take roles beyond enhancing productivity, for example, as communication mediators (Te'eni, 2001) or decision-making partners (Komiak & Benbasat, 2006). This reflects the idea of digital artifacts as applications that support tasks embedded in a certain structure and context (Benbasat & Zmud, 2003).

Natural interaction covers DTs that serve the *purpose* of enabling HMIs to be perceived as natural by humans. Again, this DT archetype is *characterized* by 'active usage', but primarily involves interaction capabilities without deeper analytics, as it mainly focuses on data 'collection' and 'transmission'. Unlike *augmented interaction*, DTs within this archetype allow for 'physical' input, enabling them to act like humans in terms of seeing, hearing, speaking, or touching. Producing 'digital (and physical)' output in 'bi-directional' 'one-to-one' interactions, this DT archetype also serves as 'application' and acts with a 'cyber-physical' scope. As an *example*, Conversational User Interfaces are a high-level design models in which user and machine interactions primarily occur in the user's spoken or written natural language. These interactions range from simple utterances to highly complex interactions and results (Gartner Inc., 2017). A similar example is Natural-language Question Answering, a type of natural-language processing technology providing users with a means of asking a question in plain language. A computer or service can answer it meaningfully, while maintaining the flow of interaction (Gartner Inc., 2016). This DT archetype relates to the social actor view (Al-Natour & Benbasat, 2009). From the perspective of anthropomorphic IS, DTs are seen as social actors, which possess "human-like physical or non-physical characteristics, behaviors, emotions, traits and attributes" (Pfeuffer, Benlian, Gimpel, & Hinz, 2019). As a result, users perceive interactions with DT as interpersonal and react as if they were interacting in social situations (Al-Natour & Benbasat, 2009; Kelley et al., 2003).

To shed light on the assignment process of DTs to purpose-related archetypes, we provide an overview of the unique combinations of characteristics for each archetype, shown in Table 4. For each archetype, we provide a statement that uses the logical operators 'AND' and 'OR' (Boell & Cecez-Kecmanovic, 2014) to combine a set of characteristics from our taxonomy. The results show that assigning DTs to archetypes does not necessarily require specifying all characteristics.

Table 4. Unique Combination of Characteristics for each Archetype

Purpose-related DT archetype	Unique combination of characteristics
Connectivity & Computation	Role of Technology = ‚Infrastructure' ***AND*** { Multiplicity = ‚Many-To-Many' ***OR*** Human Involvement = „Passive Usage" }
Platform Provision	Role of Technology = ‚Infrastructure' ***AND*** { Multiplicity = ‚One-To-Many' ***OR*** { Scope = ‚Cyber' ***AND*** Human Involvement = ‚Active Usage' }}
Personal Mobile Communication	Role of Technology = ‚Infrastructure' ***AND*** { Multiplicity = ‚One-To-One' ***OR*** Data Treatment = ‚Collection/Transmission' ***OR*** Input = „Digital/Physical' ***OR*** Output = Physical }
Sensor-based Data Collection	Role of Technology = ‚Application' ***AND*** { Direction = ‚Uni-Directional' ***AND*** { Data Treatment = ‚Collection' ***OR*** Input = ‚Physical' ***OR*** Output = ‚Digital' }}
Actor-based Data Execution	Role of Technology = ‚Application' ***AND*** { Data Treatment = ‚Execution' ***OR*** { Direction = ‚Uni-Directional' ***AND*** { Input = ‚Digital' ***OR*** Output = ‚Physical' }}}
Analytical Insight Generation	Role of Technology = ‚Application' ***AND*** { Scope = ‚Cyber ***OR*** Data treatment = ‚Analysis' }
Self-dependent Material Agency	Role of Technology = ‚Application' ***AND*** { Multiplicity = ‚One-To-Many '***OR*** Input = ‚Digital/Physical' ***OR*** Output = ‚Digital/Physical' ***OR*** Data Treatment = 'Collection/Analysis/Execution/Transmission'}
Augmented Interaction	Role of Technology = ‚Application' ***AND*** { Data Treatment = ‚Transmission' ***OR*** { Direction = ‚Bi-Directional' ***AND*** Output = ‚Physical' }}
Natural Interaction	Role of Technology = ‚Application' ***AND*** { Direction = ‚Bi-Directional ***AND*** { Data Treatment = ‚Collection' ***OR*** Input = ‚Physical' ***OR*** Output = ‚Digital' }}

6 Evaluation and Application

To evaluate the taxonomy, we first assessed its reliability by classifying the DTs from our sample and by calculating hit ratios (Appendix F). To that end, two co-authors independently classified the DTs. They achieved dimension-specific hit ratios of more than 84%. Moreover, 80% of the object-specific hit ratios exceeded 75%. These results support the taxonomy's ability to classify individual DTs.

Second, to evaluate the purpose-related DT archetypes, we assessed their reliability and validity through the Q-sort method. As for the internal Q-sort, we achieved an overall hit ratio of 88% (Moore & Benbasat, 1991) and a Cohen's Kappa of 84% (Cohen, 1960), reflecting 'almost perfect' agreement (Landis & Koch, 1977). Indicating the extent to which the DTs from our sample were correctly classified, the archetype-specific hit ratios amounted to at least 71%. As for the external Q-sort, the industry experts received an overall hit ratio of 75% (Moore & Benbasat, 1991) and a Fleiss' Kappa of 61% (Fleiss, 1971), reflecting 'substantial' agreement (Landis & Koch, 1977). Hence, we consider the DT archetypes valid and reliable.

Third, during the external Q-sort, we also asked the industry experts to assess the perceived usefulness of the taxonomy and archetypes. The experts confirmed that, from their perspective, both artifacts cover the full range of DTs, and that the dimensions and characteristics of the taxonomy and the purpose-related nomenclature of the archetypes are easy to understand. Regarding applicability, the experts shared their ideas for using the taxonomy and archetypes. On the one hand, they argued that DT has long been an integral part of their organizations' strategic considerations. Hence, they stated that both artifacts would help to stimulate and structure strategic discussions among organizational stakeholders, e.g., Chief Technology or Digital Officers (CTO and CDO), product designers, or technical solution architects. For instance, the taxonomy and archetypes could be transferred into a monitoring tool to track current DT usage and identify 'blind spots' of DT purposes as input for respective discussions. Along these lines, the archetypes' purpose-related perspective is considered particularly useful for communicating with the (non-technical) senior management, for which detailed discussions about a DT's technical features are rarely necessary. On the other hand, the experts highlighted that the taxonomy and archetypes might also be used to systematically screen technological trends on the market to identify relevant emerging DTs. Organizations might even use the taxonomy and archetypes to support their DT design efforts, e.g., as a strategic compass to design DTs serving existing or new purposes in their business context. In Sections 7.3 and 7.4, we revisit the experts' feedback and ideas when discussing managerial implications of our results and potential future research.

Fourth, in line with the organizational systematics paradigm (McKelvey, 1982; Ross, 1974), we challenged the archetypes' robustness over time by examining their year-wise occurrence in the GHC. While our sample used for developing the taxonomy and archetypes covered the years 2009 to 2017, this analysis comprised the years 2000 to 2020 to assess whether the archetypes also apply to DTs beyond the original sample used for their development (i.e., test data). To that end, two co-authors independently mapped 191 related DTs to our archetypes, yielding 'almost perfect' agreement (Landis & Koch, 1977). This result strengthens our confidence that the purpose-related DT archetypes are sufficiently concrete to appropriately reflect the purpose diversity of DTs over time and, at the same time, sufficiently abstract to be persistence over a reasonably long period of time, even beyond the considered time frame for development.

This longitudinal analysis also enabled us to better understand the evolution of the DT construct and its diverse purposes over time. Figure 3 shows three time slices comprising seven consecutive years of the GHC each, yielding the following insights: On the one hand, *infrastructure* technologies including *connectivity & computation*, *platform provision,* and *personal mobile communication* have accounted for almost 60% of DTs at the beginning of the millennium. To date, they have lost significant share or even disappeared from the GHC as in the case of *personal mobile communication*. Disappearance, however, does not mean that the DTs have disappeared from the market. Rather, it refers to an end of the listing as an emerging DT in the GHC. On the other hand, the shares of *application* technologies have significantly increased such that the overall distribution of DT archetype is much more balanced. In particular, the shares of *intelligence* technologies (e.g., *analytical insight generation*) and *interaction* technologies (e.g., *natural interaction*) have grown, and *self-dependent material agency* has emerged as a novel DT archetype of *intelligence* technologies. In sum, the longitudinal analysis reflects the evolution of the DT construct from a rather concentrated to a more balanced and purpose-diverse distribution, whereas it is noteworthy that most DT archetypes have already been present in early editions of the GHC.

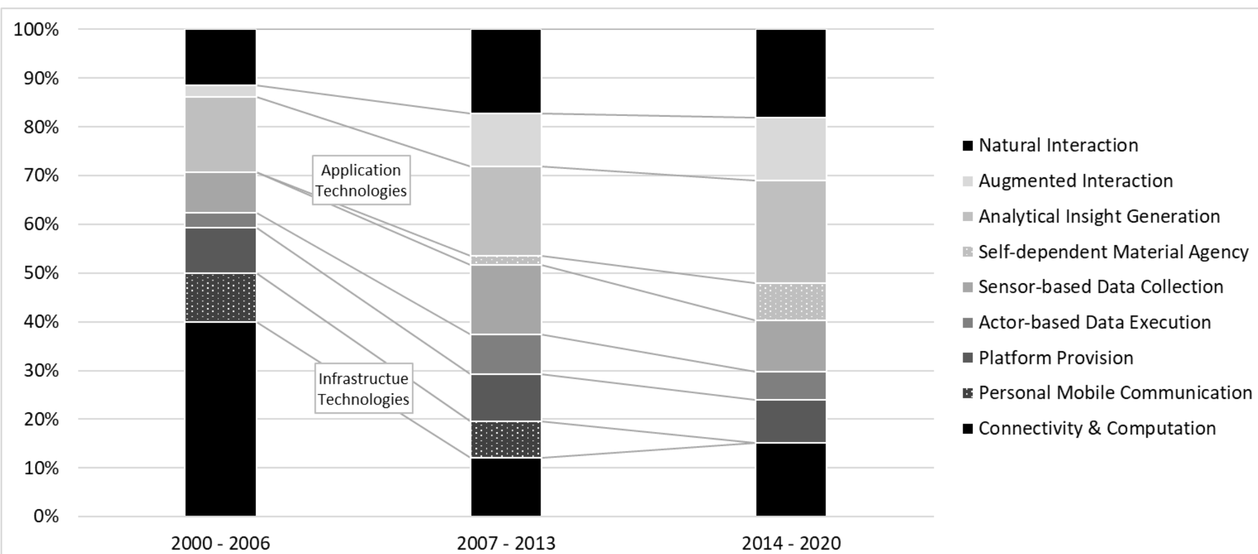

Figure 4. Distribution of the Purpose-related Archetypes between 2000 and 2020

7 Discussion

7.1 Contribution

Although purpose is an inherently important aspect of DT's nature and use in practice (Ciriello et al., 2019; Faulkner & Runde, 2019; Hund et al., 2021), a classification of DTs through their diverse purposes is missing. As we are convinced that IS researchers and practitioners would benefit from a purpose-related classification of DTs (Gregor, 2006; Kundisch et al., 2021), we set out to study *how DTs can be classified through their purposes*. To address this question, we followed an organizational systematics paradigm (McKelvey, 1982) and built a taxonomic theory for DT, comprising two artifacts. First, we followed Nickerson et al. (2013) to develop a multi-layer taxonomy for DT incorporating 8 dimensions and 20 characteristics. The taxonomy enables the classification of individual DTs assessing similarities and differences. Second, we used the taxonomy and applied a cluster analysis to inductively develop nine purpose-related DT archetypes, which can be further differentiated into *infrastructure* and *application* technology. We drew from justificatory knowledge to substantiate each archetype and empirically validated both artifacts (i.e., the taxonomy and the archetypes) during an intensive evaluation.

In line with Gregor (2006) and Gregor and Hevner (2013), we understand the presented taxonomic theory as a theory for analyzing that contributes to IS research in three ways. First, our results are a useful foundation for other scholars as we not only consolidated many years of profound discourse and data on DT but also added to the descriptive knowledge on DT. We thereby argue that the taxonomic theory exceeds existing technology classifications by being the first that (1) has been rigorously developed, (2) considers the nature of DT, (3) is sufficiently concrete to reflect the diverse purposes of DT, and (4) is sufficiently abstract to be persistent (over a reasonably long period of time). Second, our results reinforce the importance of discussing the purpose of DTs by shifting from a purely technical to a purpose-related perspective that considers the interplay of technology, task, and human (Zigurs & Buckland, 1998). In this regard, our findings directly build on and advance preliminary work by Faulkner and Runde (2019) and Hund et al. (2021), as we structure and specify the purposes that DT can acquire as part of its social positioning. The taxonomic theory also comprises easily applicable mechanisms to categorize established and emergent DTs (Laycey et al., 2019) based on their purpose. For example, we specified which characteristics of DT (i.e., as listed in the taxonomy) are unique for each archetype. We argue that our taxonomic theory, especially the taxonomy underlying the purpose-related archetypes, supports such classifying mechanisms for DT and its diverse purposes which reaches beyond existing technology classifications. Third, we built and followed an unusual research approach by analyzing DTs close to practice, i.e., using the GHC as a data source, and by combining multiple methodological components. Our study may, hence, motivate other scholars to follow our approach addressing similar problems or serve as a blueprint on how combining research methods in a new manner can generate novel insights for existing phenomena.

7.2 Theoretical Implications

Our work connects to the ongoing discussions on the nature of DT (Faulkner & Runde, 2019; Kallinikos et al., 2013) and its purposes in social contexts (Ciriello et al., 2019; Hund et al., 2021). Along these lines, our theoretical implications are twofold, 1) advancing our understanding of the diverse purposes of DT a well as 2) laying the ground for further theorizing around the DT construct.

7.2.1 Advancing our Understanding of the diverse Purposes of DT

Our work extends existing knowledge on the nature of DT (e.g., Baskerville et al. (2020), Kallinikos et al. (2013), and Yoo et al. (2010)) targeting the diverse purposes of DT. Our taxonomic theory, thereby, is not only useful for describing but also valuable for analyzing the past and future development of DT purposes. More precisely, based on a longitudinal analysis as part of our evaluation (McKelvey, 1982), we demonstrated its usefulness for providing insights into the (historical) evolution of the DT construct and the shift from IT to DT. Although we only used a sub-set (i.e., 92 DTs from 2009 to 2017) of the full sample of DTs from the GHC between 2000 and 2020 to develop the taxonomy and DT archetypes, all 191 DTs could be sorted to one of the DT archetypes and most archetypes have been reflected across the years (from the beginning of the GHC in 2000) with varying shares. These varying shares reflect the growing purpose diversity of DTs. While the share of *infrastructure* technologies (e.g., connectivity & computation) accounted for almost 60% from 2000 to 2006, DTs have spread across *application* technologies (e.g., self-dependent material agency) such that the distribution of the DT archetypes is much more balanced today. In this regard, the traditional understanding of IT as a collector, storage, processor, and transmitter of information (Boaden & Lockett, 1991) can be associated with the identified *infrastructure* technologies.

Our analysis confirms the shift from a predominance of *infrastructure* technologies to an almost equal distribution of DT archetypes today. The existence of such a shift has already been mentioned in previous seminal studies, e.g., in Hirschheim and Klein's (2012) and Baskerville et al.'s (2020) descriptions of IS research history. While one part of the IS field traditionally focused on improving hardware components, another focused on improving usability of the information provided by IT. To do so, researchers and practitioners had to push the limits of what technologies could do, leading to the emergence of novel technologies that support new purposes such as decision making, knowledge management or business intelligence. Our work, on the one hand, offers further orientation for distinguishing IT from DT in terms of purpose diversity (Baskerville et al., 2020). On the other hand, we find that today's DT construct still covers novel *infrastructure* technologies (e.g., 5G or Quantum Computing). Our findings therefore suggest that—although there is a growing share of *application* technologies—one should not neglect *infrastructure* technologies (i.e., traditionally referred to as IT) needed for representing and modelling reality. These DTs continue to be the foundation for digital opportunities, not only for single corporations but for entire industries and economies. With this, we contribute to but also plead for a more differentiated perspective on the DT construct.

7.2.2 Laying the Ground for further Theorizing around the DT Construct

Our work accumulates and structures a lot of data about DT which facilitates further theorizing on the DT construct in three ways. First, by being sufficiently concrete to be useful and sufficiently abstract to be robust, our taxonomic theory enables researchers to theorize beyond the level of individual DTs and focus on purpose-related DT archetypes. To do so, the taxonomy provides a nomenclature for scholars to be consistent and specific when referring to DT. By being consistent regarding DT terminology and meaning, it becomes easier to understand which discussion in the literature a DT-related study joins, how it compares to the existing body of knowledge (e.g., where it overlaps or contradicts), and consequently what knowledge new findings add. Moreover, we can use the taxonomic theory to accumulate and structure even more data around specific purposes of DT in the future. Further, IS researchers can be specific in characterizing the DT and the context they are studying (Benbasat & Zmud, 2003; Orlikowski & Iacono, 2001), facilitating discussions around the generalizability of results (Lee & Baskerville, 2003) and avoiding ambiguous results that lack contextualization (Hong, Chan, Thong, Chasalow, & Dhillon, 2014).

Second, the taxonomic theory would allow for more precise explanations (e.g., towards a Type II theory) of the effects of DT for different phenomena. For example, focusing on digital entrepreneurship, Kreuzer et al. (2022) identified effects of DT on opportunity recognition based on a high-level understanding of DT. Further research could leverage our results to differentiate what effects arise from which DT purposes. In a similar way, the work by Oberländer et al. (2021) – which developed classes of digital opportunities and stylized facts of opportunity conversion – could be extended by understanding which DT archetypes drive which digital opportunity classes. Such an approach, based on our taxonomic theory, may also be used to advance long-standing and nascent IS theories, e.g., technology acceptance (Venkatesh & Bala, 2008; Venkatesh, Morris, & Davis, 2003) or (dis-) continuance of use (Bhattacherjee, 2001; Mehrizi, Rodon, & Mezhad, 2019). Instead of building on a general idea of DT, building on our taxonomic theory could lead to more robust results on the level of purpose-related DT archetypes while also being much more concrete. Further, the taxonomic theory allows for investigating the relationships among DT purposes, industrial and/or organizational contexts, as well as related implementation requirements or success factors. In doing so, IS research can, for example, examine the hypothesis that some purposes are more suitable than others to develop digital innovation or to drive digital transformation in specific industries.

Third, the taxonomic theory as a theory for analyzing (Gregor, 2006; Gregor & Hevner, 2013) represents a fundamental step towards other types of theory, i.e., theories for predicting (i.e., Types III– IV) as well as design and action (i.e., Type V). Regarding prediction, other researchers can, for example, use the findings of the longitudinal analysis to theorize on how purposes of DT will evolve in the future. Regarding design and action, other researchers could study whether there are distinct design principles underlying DT archetypes and how each principle influences the extent to which a DT fulfills its desired purpose. These design principles could be, for example, used to develop guidelines or best practices for designing DT serving specific purposes. Moreover, such design principles may serve as valuable input for design science research to span the solution space for the development of novel digital artifacts (Gregor & Hevner, 2013).

7.3 Managerial Implications

From the standpoint of practice, our paper also provides a relevant contribution (Corley & Gioia, 2011; Moeini, Rahrovani, & Chan, 2019) with major implications for managers that are involved in DT decision-making. On the one hand, this may be a technology consultant that specializes in supporting organizations, for example, in the evaluation of their current technology portfolio or in make-or-buy-decision. On the other hand, this may be an executive responsible for an organization’s technological and digital matters, i.e., a CTO or CDO. The roles of CTO and CDO have gained increasing strategic importance as a driver of organizational performance (Medcof & Lee, 2017; Tumbas, Berente, & vom Brocke, 2018). A CTO’s tasks include, among others, aligning “technology strategy with corporate strategy and business model”, selecting “technologies to adopt or discard”, and managing “new technology development” (Medcof & Lee, 2017, p. 4). Complementary, a CDO’s tasks revolve around “developing the emerging digital logic of action, and […] enacting this digital logic through strategies such as grafting, bridging, and decoupling to navigate tensions between the existing and emerging approaches to innovation with digital technologies” (Tumbas et al., 2018, p. 188). Considering these “personas” and their responsibilities, we argue that our results yield three major practical implications for managers.

Managers should leverage the taxonomy and archetypes to assess the current DT portfolio in an organization. Using our results, technology consultants can determine the status quo of DT usage in an organization by determining which purposes the DT portfolio currently covers (McKeen & Smith, 2002, 2006). In doing so, they may be able to locate blind spots, i.e., missing elements that are crucial to support or enable the corporate strategy, more effectively. Using our taxonomic theory, the identification of key technologies, which create competitive advantages or are essential for business operations, becomes feasible. In line with McKelvey (1982), CTOs should also track their organization’s DT usage over time. While practitioners have been facing the variety of DTs in terms of technology lists and trend reports (Adomavicius et al., 2008), thinking in terms of DT archetypes enables and improves the structured handling and discussion of DTs in everyday business.

Managers should shift their perspective on DT investment decisions from a technical to a purpose perspective. Deciding on the right DT investment to address a current problem or opportunity is one of the core tasks of a technology consultant, CTO and CDO. As there are many factors that influence an investment decision, e.g., cost or effectiveness, it is easy to get lost in comparing detailed technical functionalities of individual DTs or requirements. Further, there might be a bias towards one technology that is “en vogue” at that point in time. In line with our purpose-related perspective, we propose that managers should abstract from specific functionalities or requirements and think about the overarching purpose a solution should have. For example, managers could follow a stepwise approach to make DT investment decisions, referring to the purpose-related DT archetypes as long as possible, before evaluating and prioritizing individual DTs therein from a task-technology-fit perspective in further detail (Denner et al., 2018). This will enhance both the efficiency and effectiveness of DT decisions

Managers should use the taxonomy and archetypes to develop and design DT. In line with Gross et al. (2021), we argue that our taxonomy can be seen as a design space (MacLean, Young, Bellotti, & Moran, 1991) providing a structured overview of designs choices for the development of DTs. On the one hand, organizations might need a DT for a specific purpose. Managers can then use our taxonomic theory to identify the (usual) characteristics of DTs serving this purpose and design the solution accordingly, e.g., based on design principles underlying each DT archetype (see Section 7.2.2). On the other hand, organizations might face a complex challenge that requires them to combine multiple DT purposes into a novel technical solution as part of a product or service. To do so, managers can decide on a suitable set of DT archetypes, screen all DTs that serve the respective purposes, and select the most fitting ones, e.g., in terms of affordability or availability.

7.4 Limitations and Further Research

Although we believe that our findings offer significant insights regarding the DT construct, as any research, our findings are beset with limitations.

First, we argued that our taxonomic theory is sufficiently abstract to be persistent over a reasonably long period of time and hope that it is useful for at least one generation of technological evolution in its current form. However, in line with seminal work on taxonomy research by Bailey (1994), Nickerson et al. (2013), and Kundisch et al. (2021), there are limits to any taxonomy in a changing environment. This is especially true for such a dynamic topic as digitalization, which is often seen as a catalysator for but also prone to volatility, uncertainty, complexity, and ambiguity (Buckley, 2020). Hence, we cannot ensure that the developed categories will resist any technological change in the future. Continuing to apply an outdated taxonomic theory entails risks, e.g., when it is used to build other more advanced types of theory. To counteract this issue and remain useful, taxonomies should be adaptable and extendible (Nickerson et al., 2013). Therefore, we recommend that future research periodically evaluates whether our taxonomic theory is still valid and, if necessary, updates it by using our thorough descriptions of the development process and corresponding data.

Second, there are limitations resulting from our research design decisions. On the one hand, we developed the taxonomy and purpose-related DT archetypes based on a sample of 92 DTs covering the 2009 to 2017 editions of the GHC as primary data source. We are convinced that the sample has been compiled with due care as we used other technology reports for cross-checking purposes and the GHC between 2000 and 2020 for evaluation. However, the specific compilation of the sample may have influenced our findings and we cannot formally exclude subjective bias in the author team when interpreting the DT definitions provided in the GHC. Moreover, there might be technologies outside the GHC that could be categorized as DTs and, thus, deserve scrutiny and classification based on their purpose. On the other hand, owing to the fast-moving nature and diversity of DTs, we developed the purpose-related DT archetypes inductively. As a result, the delineation among the archetypes is not as sharp as if we had developed them deductively, which was also highlighted by the experts during the Q-sort. To some extent, one could argue that our archetypes reflect the way people see and categorize DTs (i.e., from a purpose perspective), and not necessarily the technical aspects that distinguish one DT from another. Moreover, identifying meaningful, purpose-related names for the DT archetypes was an interpretative task and, in the end, subjectively influenced – even if the entire author team was involved and the names were validated by industry experts. Future research may critically challenge the aspects of our research that are prone to subjectivity e.g., by following a similar approach based on another sample of DTs or by developing and validating competing nomenclatures.

Third, there are limits to our taxonomic theory as it has not been tested in actual application. Although we highlighted some ideas for practical application of our results in Section 7.3, these ideas are based on the results of the external Q-sort, and the creativity and limited experience of the authors. While testing these ideas exceeds the scope of our research, future work may build prototypes or methods for our taxonomic theory and apply them in practice. This will provide further insights into the usefulness of approaches that take a purpose perspective on DT and may stimulate a new way of thinking and discussing technology.

8 Concluding Remarks

Given the growing number and diversity of DTs as well as the increasing research on digitalization, we believe that it is our responsibility as IS scholars to advance our understanding of DT, a construct located at the heart of the discipline. We see our research as an important step towards this goal. To the best of our knowledge, our taxonomic theory presents a novel purpose-related understanding and classification of DT that bridges the gap between individual DTs and the general umbrella term and allows for a structured analysis of DT through its diverse purposes. The DT archetypes may be used to contextualize existing IS theories and serve as foundation for future sense-making and design-oriented research. In practice, they may help mangers to assess and select DTs in a clear-headed manner based on their purposes instead of having to rely on ephemeral technology lists and trend reports.

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Appendix A: Comparison of Existing Technology Classifications

To emphasize the need for a purpose-related classification and to outline the existing knowledge base, we compare existing technology classifications from academia and practice according to four criteria that are relevant for classifying DT through its purposes: 1) Rigorously developed, 2) applicable to DT, 3) sufficiently concrete to reflect the diverse purposes of DT and 4) sufficiently abstract to be persistent. We considered existing technology classifications from the academic IS literature as well as professional literature, which offer more tangible yet a-theoretical approaches. In Table A1, we present a list of all technology classifications which we considered. We name the term they use for technology, list the classes or categories they provide, and give an assessment which of the four criteria they address. While our list may be not exhaustive, we are confident that it covers a relevant and representative sample. We find that, a digital technology classification that addresses all four criteria is yet missing.

Table A1. Technology Classifications

Paper	Term	Classes/Categories	1) *	2) *	3) *	4) *
Accenture, 2019	DT	Distributed ledger, Artificial Intelligence, Extended Reality, and Quantum Computing		X		X
Agrawal, Chari, & Sankar, 2003	Wireless Technology	Data rate, modulation, frequency band, logical topology, compatibility with previous generations	X		X	
Bharadwaj, El Sawy, Pavlou, & Venkatraman, 2013	DT	Information, Computing, Communication, and Connectivity	X	X		X
Davis, 2000	IT	Infrastructure, Repositories, or Applications for Transaction, Processing, Operations, Administration, or Management	X		X	X
Evans, 2016	Technology	Social, Mobile, Analytics, Cloud		X		X
Fitzgerald, Kruschwitz, Bonnet, & Welch, 2014	DT	Social media, mobile, analytics, embedded devices		X		X
Hevner & Park, 2004	IT Artifact	Constructs, Models, Methods, Instantiations				
Janssen, Passlick, Rodríguez Cardona, & Breitner, 2020	Virtual Assistance	Goal-oriented daily chatbot, non-goal-oriented daily chatbot, utility facilitator chatbot, utility expert chatbot, relationship-oriented chatbot	X	X	X	
Kling & Scacchi, 1982	Computer Technology	Computing resource, infrastructure	X			X
Kohli & Sherer, 2002	IT	Operational IT, Managerial IT, Strategic IT	X			X
Nevo, Nevo, & Ein-Dor, 2010	IT	Commerce and Transaction, Product Design and Development, Internal Focus, External Focus, Operational, Decision Support Systems	X			X
Orlikowski & Iacono, 2001	IT Artifact	Tool, Proxy, Computational, Ensemble, Nominal	X		X	X
Sebastian, Moloney, Ross, & Fonstadt, 2017	DT	Social, Mobile, Analytics, Cloud, Internet of Things, Platforms		X		X
Power, 2004	Decision Support Systems	Dominant Component, Targeted User, Purpose, Deployment and Enabling Technology	X			
Sawyer & Huang, 2007	Technology	Feature, Function, Proxy, Proof of Concept, Presence/Absence	X		X	

Shim, Sharda, French, Syler, & Patten, 2020	IoT	Utilities, Supply Chain, Logistics, Transportation, Consumer Electronic, Public Sector, Smart Cities, Smart Buildings, Industrial Automation	X	X		
Van der Valk, Haße, Möller, & Otto, 2021	Digital twin	Data Acquisition, Data Source, Synchronization, Data Input, Data Governance, Data Link, Interface, Interoperability, Purpose, Accuracy, Conceptual Elements, Time of Creation	X	X	X	
Vial, 2019	DT	Social, Mobile, Analytics, Cloud, Internet of Things, Platforms	X	X		X
Yang & Tate, 2012	Cloud Computing	Service Levels, Deployment Models, Essential Characteristics	X	X	X	
Yoo, Henfridsson, & Lyytinen, 2010	DT	Content, Service, Network, Device	X	X		X
*Note: 1) Rigorously developed, 2) applicable to DT, 3) sufficiently concrete to reflect the diverse purposes of DT and 4) sufficiently abstract to be persistent.						

Appendix B: Sample of Digital Technologies

Table B1 lists all technologies included in the GHC from 2009 to 2017. The column 'year of publication' indicates in which years each technology appeared. The second set of columns lists the assessment requirements, based on which we compiled the sample of digital technologies that we used as the foundation for the development of our taxonomy. We checked (in a binary manner, i.e., yes or no) whether a technology (1) is assessable based on publicly available information, (2) is on the 'approach' layer as defined in the manuscript, and (3) complies with the properties of DTs as per Yoo et al. (2010). We checked these requirements in the given order and stopped as soon as one of the requirements was not met. A technology was included and referred to as a DT, if it met all requirements. Thirdly, the 'additional sources' columns show in which other technology reports a technology was included. The column 'sample of classification' shows in which iterations of our taxonomy development process a technology was considered. The last column indicates which purpose-related archetype a technology has been assigned to

Table B1. List of Examined Technologies from the Gartner Hype Cycle for Emerging Technologies from 2009 to 2017.

		Year of Publication (Gartner Hype Cycle for Emerging Technologies)									Assessment Require-ments**			Additional Sources for Technologies***								Sample for Classification		
No.	Technology*	2017	2016	2015	2014	2013	2012	2011	2010	2009	Sufficient Information	Level of Granularity	Properties of DT	Accenture	Deloitte	Forbes	Forrester	Future Today Institute	MIT Technology Review	Scientific America	World Economic Forum	Iteration 2 & 3	Iteration 2, 3, 4 & 5	Purpose-related DT Groups
1	3D Bioprinting Systems for Organ Transplant / 3D Bioprinting Systems / 3D Prioprinting			x	x	x	x	x			yes	yes	yes					x	x			x	x	Actor-based Data Execution
2	3D Flat-Panel TVs and Displays / 3D Flat-Panel Displays								x	x	yes	yes	yes										x	Actor-based Data Execution
3	3D Printing						x	x	x	x	yes	yes	yes					x	x	x	x		x	Actor-based Data Execution
4	3D Scanners				x	x	x				yes	yes	yes					x					x	Sensor-based Data Collection
5	4D Printing	x	x								yes	yes	yes							x	x	x	x	Actor-based Data Execution
6	4G Standard								x		yes	yes	yes										x	Connectivity & Computation
7	5G	x									yes	yes	yes			x						x	x	Connectivity & Computation
8	802.11ax		x								yes	yes	yes									x	x	Connectivity & Computation
9	Activity Streams				x	x	x	x	x		yes	yes	yes										x	Analytical Insight Generation
10	Advanced Analytics with Self-Service Delivery			x							yes	yes	yes		x	x		x				x	x	Augmented Interaction
11	Affective Computing		x	x	x	x					yes	yes	yes					x				x	x	Natural Interaction
12	Application Stores/Mobile Application Stores						x	x	x		yes	yes	yes										x	Platform Provision
13	Artificial General Intelligence / General-Purpose Machine Intelligence	x	x								yes	no	-											
14	Augmented Data Discovery / Smart Data Discovery	x	x								yes	yes	yes			x		x				x	x	Augmented Interaction
15	Augmented Reality	x	x	x	x	x	x	x	x	x	yes	yes	yes		x	x		x	x			x	x	Augmented Interaction
16	Automatic Content Recognition						x				yes	yes	yes					x					x	Natural Interaction
17	Autonomous Field Vehicles			x							yes	yes	yes					x				x	x	Self-dependent Material Agency
18	Autonomous Vehicles	x	x	x	x	x	x		x		yes	yes	yes					x	x	x	x	x	x	Self-dependent Material Agency
19	Behavioral Economics									x	yes	no	-											
20	Big Data / "Big Data" and Extreme Information Processing and Management				x	x	x	x			yes	no	-											
21	Bioacoustic Sensing			x	x	x					yes	yes	yes									x	x	Sensor-based Data Collection
22	Biochips			x	x	x					yes	yes	yes					x				x	x	Sensor-based Data Collection
23	Biometric Authentication Methods					x	x	x	x		yes	yes	yes					x					x	Sensor-based Data Collection
24	Blockchain	x	x								yes	yes	yes		x	x	x	x		x	x	x	x	Connectivity & Computation
25	Brain Computer Interface / Computer-Brain Interface	x	x	x	x	x	x	x	x		yes	yes	yes					x	x		x	x	x	Sensor-based Data Collection
26	Broadband over Power Lines								x		yes	yes	yes										x	Connectivity & Computation
27	BYOD (Bring your own device)						x				yes	no	-											
28	Citizen Data Science			x							yes	yes	yes					x				x	x	Analytical Insight Generation
29	Cloud/Web Platforms							x	x		yes	yes	yes	x	x		x	x					x	Platform Provision
30	Cloud Computing				x	x	x	x	x	x	yes	no	-											
31	Cognitive Computing	x									yes	no	-											
32	Cognitive Expert Advisors	x	x								yes	yes	yes					x				x	x	Augmented Interaction
33	Complex Event Processing				x	x	x				yes	yes	yes										x	Analytical Insight Generation
34	Commerical UAVs (Drones)	x	x								yes	yes	yes					x	x	x	x	x	x	Natural Interaction
35	Connected Home	x	x	x	x						yes	no	-											
36	Consumer 3D Printing			x	x	x					yes	yes	yes					x				x	x	Actor-based Data Execution
37	Consumer-generated Media								x		yes	no	-											
38	Consumer Telematics				x	x	x				yes	no	-											
39	Consumerization						x	x			yes	no	-											
40	Content Analytics				x	x					yes	no	-											
41	Context-enriched Services							x			yes	yes	yes										x	Analytical Insight Generation
42	Context Brokering		x								no	-	-											
43	Context Delivery Architecture								x	x	yes	no	-											
44	Conversational User Interfaces	x	x								yes	yes	yes					x	x			x	x	Natural Interaction
45	Crowdsourcing						x				yes	no	-											

		Year of Publication (Gartner Hype Cycle for Emerging Technologies)									Assessment Require-ments**			Additional Sources for Technologies***								Sample for Classification		
No.	Technology *	2017	2016	2015	2014	2013	2012	2011	2010	2009	Sufficient Information	Level of Granularity	Properties of DT	Accenture	Deloitte	Forbes	Forrester	Future Today Institute	MIT Technology Review	Scientific America	World Economic Forum	Iteration 2 & 3	Iteration 2, 3, 4 & 5	Purpose-related DT Groups
46	Cryptocurrencies			x	x						yes	yes	yes									x	x	Platform Provision
47	Cryptocurrency Exchange			x							yes	yes	yes									x	x	Platform Provision
48	Corporate Blogging									x	yes	no	-											
49	Data Broker PaaS		x								yes	yes	yes		x							x	x	Platform Provision
50	Data Science				x						yes	no	-											
51	Deep learning	x									yes	yes	yes				x	x	x	x	x	x	x	Analytical Insight Generation
52	Deep Reinforcement Learning	x									yes	yes	yes					x	x			x	x	Analytical Insight Generation
53	Digital Dexterity			x							no	-	-											
54	Digital Security			x	x						yes	no	-											
55	Digital Twin	x									yes	yes	yes									x	x	Natural Interaction
56	E-Book Readers							x	x	x	yes	yes	yes										x	Personal Mobile Communication
57	Edge Computing	x									yes	yes	yes			x	x	x				x	x	Connectivity & Computation
58	Electronic Paper								x	x	yes	yes	yes										x	Augmented Interaction
59	Electrovibration					x					yes	no	-											
60	Enterprise 3D Printing			x	x	x					yes	yes	yes					x				x	x	Actor-based Data Execution
61	Enterprise Taxonomy and Ontology Management	x	x								yes	yes	yes				x					x	x	Analytical Insight Generation
62	Extreme Transaction Processing								x		yes	no	-											
63	Gamification				x	x	x	x			yes	no	-											
64	Gesture Control Device/Gesture Control		x	x	x	x	x				yes	yes	yes					x				x	x	Natural Interaction
65	Gesture Regocnition							x	x		yes	yes	yes					x					x	Sensor-based Data Collection
66	Green IT									x	yes	no	-											
67	Group Buying							x			yes	no	-											
68	Home Health Monitoring						x			x	yes	no	-											
69	Hosted Virtual Desktops						x	x			yes	yes	yes										x	Connectivity & Computation
70	HTML5						x				yes	yes	no											
71	Human Augmentation	x	x	x	x	x	x	x	x	x	yes	no	-											
72	Hybrid Cloud Computing			x	x		x				yes	yes	yes		x							x	x	Platform Provision
73	Idea Management						x	x	x	x	yes	no	-											
74	Image Recognition							x			yes	yes	yes			x		x					x	Natural Interaction
75	In-memory Analytics				x	x	x				yes	yes	yes		x			x					x	Analytical Insight Generation
76	In-memory Database Management Systems				x	x	x	x			yes	yes	yes		x								x	Analytical Insight Generation
77	Interactive TV								x		yes	yes	yes					x					x	Augmented Interaction
78	Internet Micropayment Systems								x		no	-	-											
79	Internet TV						x	x	x	x	yes	yes	yes					x					x	Augmented Interaction
80	IoT			x	x	x	x	x			yes	yes	yes		x	x		x				x	x	Connectivity & Computation
81	IoT Platform	x	x	x							yes	yes	yes	x	x			x				x	x	Platform Provision
82	Location Intelligence/Location-Aware Applications					x		x	x	x	yes	yes	yes					x					x	Natural Interaction
83	Machine-to-Machine Communication Services				x	x	x	x			yes	yes	yes		x	x		x	x				x	Connectivity & Computation
84	Machine Learning	x	x	x							yes	yes	yes	x	x	x	x	x				x	x	Analytical Insight Generation
85	Media Tablets						x	x	x		yes	yes	yes					x					x	Personal Mobile Communication
86	Mesh Networks: Sensor					x	x	x	x	x	yes	yes	yes						x				x	Sensor-based Data Collection
87	Microblogging								x	x	yes	no	-											
88	Micro Data Center		x	x							no	-	-											
89	Mobile Health Monitoring				x	x					yes	no	-											
90	Mobile OTA Payment / Over-the-Air Mobile Phone Payment Systems, Developed Markets						x			x	yes	yes	yes					x					x	Analytical Insight Generation
91	Mobile Robots					x	x	x	x	x	yes	no	-											
92	Nanotube Electronics	x	x								no	-	-											
93	Natural-Language Question Answering		x	x	x	x	x	x			yes	yes	yes					x	x	x	x	x	x	Natural Interaction
94	Neurobusiness			x	x	x					no	-	-											
95	Neuromorphic Hardware	x	x								yes	yes	yes						x	x	x	x	x	Connectivity & Computation
96	NFC (Near Field Communication)				x	x	x				yes	yes	yes					x	x				x	Connectivity & Computation
97	NFC Payment						x	x			yes	yes	yes					x	x				x	Analytical Insight Generation
98	Online Video									x	yes	yes	yes					x					x	Platform Provision
99	Pen-Centric Tablet PCs								x		yes	yes	yes										x	Personal Mobile Communication
100	People-Literate Technology			x							yes	yes	yes					x				x	x	Natural Interaction
101	Personal Analytics		x								no	-	-											
102	Predictive Analytics					x	x	x	x		yes	no	-											
103	Prescriptive Analytics				x	x					yes	no	-											
104	Private Cloud Computing						x	x	x		yes	no	-											
105	Public Virtual / Worlds Virtual Worlds						x	x	x	x	yes	yes	yes					x					x	Connectivity & Computation
106	Quantified Self				x	x					yes	no	-											
107	Quantum Computing	x	x	x	x	x	x	x		x	yes	yes	yes						x	x	x	x	x	Connectivity & Computation
108	QR/Color Code							x			yes	yes	yes										x	Sensor-based Data Collection
109	RFID (Case/Pallet)									x	no	-	-											
110	Serverless PaaS	x									yes	yes	yes	x	x			x				x	x	Platform Provision
111	Silicon Anode Batteries						x				yes	yes	no											
112	Smart Advisors			x	x						yes	yes	yes					x				x	x	Augmented Interaction
113	Smart Dust	x	x	x		x					yes	yes	yes					x	x			x	x	Sensor-based Data Collection
114	Smart Robots	x	x	x	x						yes	no	-											
115	Smart Workspace	x	x		x						yes	no	-											
116	SOA									x	yes	yes	yes										x	Connectivity & Computation
117	Social Analytics / Social Network Analysis						x	x	x	x	yes	yes	yes			x		x	x		x		x	Analytical Insight Generation
118	Social Software Suites									x	yes	no	-											
119	Social TV							x			yes	yes	yes					x	x				x	Augmented Interaction
120	Software-Defined Anything (SDx)		x		x						no	-	-											
121	Software-Defined Security	x	x	x							yes	no	-											
122	Speech Analytics/Audio Mining						x				yes	yes	yes		x	x	x	x					x	Sensor-based Data Collection
123	Speech-to-speech Translation			x	x	x	x	x	x		yes	yes	yes					x				x	x	Natural Interaction
124	Speech Recognition				x	x	x	x	x	x	yes	yes	yes					x					x	Natural Interaction
125	Surface Computers									x	yes	yes	yes										x	Personal Mobile Communication
126	Tablet PC									x	yes	yes	yes										x	Personal Mobile Communication
127	Tangible User Interfaces								x		yes	yes	yes					x					x	Natural Interaction
128	Terahertz Waves								x		yes	yes	yes										x	Connectivity & Computation
129	Text Analytics						x				yes	yes	yes		x	x	x	x					x	Analytical Insight Generation
130	Video Analytics for Customer Service							x			yes	yes	yes			x		x					x	Sensor-based Data Collection
131	Video Search								x	x	yes	yes	yes					x	x				x	Analytical Insight Generation
132	Video Telepresence								x	x	yes	yes	yes										x	Natural Interaction
133	Virtual Assistants	x				x		x	x		yes	yes	yes					x		x	x	x	x	Augmented Interaction
134	Virtual Personal Assistant		x	x	x						yes	yes	yes					x	x	x	x	x	x	Augmented Interaction
135	Virtual Reality	x	x	x	x	x					yes	yes	yes		x	x		x	x		x	x	x	Augmented Interaction
136	Volumetric Displays / Volumetric and Holumetric Displays	x	x	x	x	x	x				yes	yes	yes					x	x		x	x	x	Natural Interaction
137	Wearables / Wearable User Interfaces			x	x	x					yes	yes	yes					x	x		x	x	x	Natural Interaction
138	Web 2.0									x	yes	no	-											
139	Wikis									x	yes	yes	yes										x	Analytical Insight Generation
140	Wireless Power						x	x	x	x	yes	yes	no											
SUM		32	34	37	45	43	49	42	41	34	131	95	92	4	16	15	8	60	24	11	16	46	92	92

* if a technology appeared under more than one name in different hype cycles, we added the additional designations with a slash
** the reuqirements were gradually checked. If one requirement did not apply, the remaining requirements were not checked
*** additional sources for technologies were only considered for the 92 digital technologies which fulfill our formal and digital requirements

Appendix C: Development of a Taxonomy of Digital Technologies

In the following, we provide details of our five iterations. We structure the following paragraphs in accordance with the taxonomy development process as per Nickerson, Varshney, and Muntermann (2013) (Figure C1).

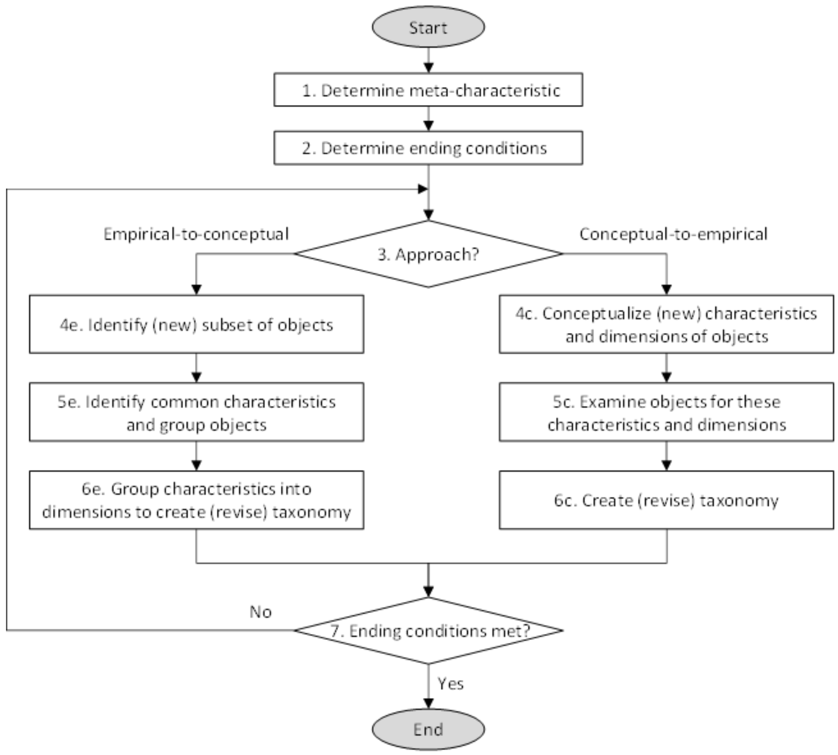

Figure C1. Taxonomy Development Method as per Nickerson et al. (2013)

Step 1: In line with our idea of using the taxonomy as a means for classifying individual DTs and for developing purpose-related DT archetypes, we chose '*characteristics of individual DTs'* as our meta-characteristic.

Step 2: As recommended by Nickerson et al. (2013), we used the following *objective ending conditions*:

(1) each characteristic is unique within its dimension,

(2) each dimension is unique and not repeated within the taxonomy,

(3) at least one object must be identified per characteristic and dimension, and

(4) an iteration does not imply further modification of the taxonomy

In line with Nickerson et al. (2013), we also chose the following *subjective ending condition*: All co-authors agree that the taxonomy is concise, robust, comprehensive, extendible, and explanatory.

After determining objective and subjective ending conditions, we chose either the conceptual-to-empirical, i.e., deductive conceptualization of dimensions and characteristics primarily based on literature and complemented by the researchers' creativity and justificatory knowledge, or the empirical-to conceptual approach, i.e., identification of a sample of real-life objects and subsequent inductive derivation of dimensions and characteristics. Figure C2 lists details on the used approaches across iterations, the corresponding sample compositions, and number of DTs per iteration along with associated methodological decisions and justification.

#	Approach	Source of sample	# of objects	Methodological Decision	Justification
1	C2E	Multiple technology and trend reports (see Table 1)	not specified	Deductive conceptualization of first layers, dimensions, and characteristics based on an extensive literature review.	Large body of literature as a starting point. Nickerson et al. (2013) recommend to build on existing works.
2	E2C	Gartner Hype Cycle (2015-2017) 09 10 11 12 13 14 15 16 17	46	Inductive classification of a sample of 46 DTs by two co-authors.	First internal evaluation based on the co-authors knowledge aquired during the literature review. Following Nickerson et al. (2013), we start with a small sample of 46 DTs which we extend in the course of the development process. We choose to look at the latest emerging technologies at the time of the clustering as these DTs are likely to include characteristics which might not be covered by older DTs.
3	E2C	Gartner Hype Cycle (2015-2017) 09 10 11 12 13 14 15 16 17	10	Inductive classification of a sample of 10 DTs by two focus groups involving IS academics. The 10 DTs are a subset of the sample used within iteration 2.	External evaluation of completeness and comprehensibility of the taxonomy. Chosen (sub)sample covers all layers, dimensions, and characteristics of the current version of the taxonomy. The subset was used to compare the results of this external evaluation with the internal evaluation within iteration 2.
4	E2C	Gartner Hype Cycle (2009-2017) 09 10 11 12 13 14 15 16 17	92	Inductive classification of an extended sample of 92 DTs by two co-authors	Internal evaluation challenging the robustness of the taxonomy by considering additional new DTs. The sample was extended due to determining whether existing layers, dimensions, and characteristics are sufficient to describe the great variety of DTs (Nickerson et al. 2013).
5	E2C	Gartner Hype Cycle (2009-2017) 09 10 11 12 13 14 15 16 17	92	Inductive classification of the extended sample of 92 DTs by two co-authors	Minor changes in iteration 4 indicate growig stability of the taxonomy. Hence, classification of the same sample as in iteration 4.

all DTs of respective year (full consideration) *a subset of DTs of respective year (partial consideration)* *no DTs of respective year (no consideration)*

Figure C2. Details on Approach, Sample Compilation, and Methodological Decisions per Iteration

Iteration 1

Step 3: As there is a large body of literature on the subject, we decided to use this as a starting point for our taxonomy development process and, consequently, applied the *conceptual-to-empirical approach*.

Step 4c: We conducted an extensive literature review, spanning from very concrete technologies such as Volumetric Displays to more abstract and general concepts such as Smart Robots. To identify DTs, we analyzed technology and trend reports (see Table B1). During this process, we found that the extent and level of detail of DT definitions varies widely across different sources. Further, certain technologies did not comply with our understanding of digital. Therefore, we developed clear assessment criteria in order to identify a sample of DTs (see 'Compiling a Sample of Digital Technologies'). As a prerequisite, each DT had to be different from any other DT. We also reduced the sample in accordance with the following formal and content-oriented requirements: (1) the definition of a DT included in the GHC had to provide sufficient information for classification, (2) the DTs had to be on the same level of abstraction, and (3) each DT had to comply with Yoo et al. (2010) DT properties of re-programmability, homogenization of data, and self-referential nature.

Based on our literature review, we conceptualized an initial superset of layers, dimensions, and characteristics, building the foundation for the following iterations. Table C1 summarizes the given definitions and justificatory references. The layers are partly based on different sources: High level (Arthur, 2009), Hype Cycle (Gartner Inc., 2009, 2010, 2011, 2012, 2013, 2014, 2015, 2016, 2017), Device (Benkler, 2006; Horvath & Gerritsen, 2012; Yoo et al., 2010), Interaction (Borgia, 2014; Fleisch, Weinberger, & Wortmann, 2014; Püschel et al., 2020), Data (Bharadwaj et al., 2013; Bucherer & Uckelmann, 2011; Porter & Heppelmann, 2014), and Service (Fleisch et al., 2014; Püschel et al., 2020; Yoo et al., 2010)

Step 5c: From the examined body of literature we identified a loose list of several different DTs and tested them against the listed characteristics in Table C1. The identified dimensions and characteristics are in line with our meta-characteristic, i.e., characteristics of DTs.

Step 6c: We grouped all of the identified dimensions and characteristics in order to create the first version of our taxonomy (see Table C1). Following the taxonomy notation of Nickerson et al. (2013), we depict a taxonomy T as a set of *n* layers L_i (i=1, …, n) with *m* dimensions D_{ij}

(j=1, …, m) each consisting of l_k ($l_k \geq 2$) characteristics C_{ijk} (k=1, …, l_k):
$T = \{L_i, i=1, \ldots, n \mid L_i = [D_{ij}, j=1, \ldots, m \mid D_{ij} = (C_{ijk}, k=1, \ldots, l_k; l_k \geq 2)]\}$

For the resulting taxonomy of the first iteration this leads to
T_1 = {*High level* [Role of Technology (Application, Component, Infrastructure)],
Hype Cycle [Development Stage (Technology Trigger, Peak of Inflated Expectations, Trough of Disillusionment, Slope of Enlightenment, Plateau of Productivity)],
Device [Scope (Cyber, Synergic, Physical)],
Interaction [Multiplicity (One-to-one, One-to-many, Many-to-many), Direction (Uni-directional, Bi-directional)],
Data [Data Treatment (Collection, Aggregation, Analysis, Execution), Input (Digital, Physical, Visual, Acoustic), Output (Digital, Physical, Visual, Acoustic)],

Service [Main Principle (Information Gathering, Efficiency Enhancement, Customer Focus, Ubiquity), Domain (Cross-sectional, Specific)]}

Step 7: The taxonomy resulting from the first iteration did not yet meet the required subjective and objective ending conditions. In particular, we were not able to identify at least one real-life object for each characteristic. Due to a large number of dimensions and characteristics, the first version was also not concise. Hence, we decided to conduct a further iteration.

Table C1. Taxonomy of Digital Technologies after Completing the First Iteration

Layer	Dimension	Characteristics and their Definition	Justificatory References
High Level	Role of Technology	Application: Provision of usability and added value on its own. Component: Creation of higher-level DTs through combination with and extension of existing DTs. Infrastructure: Enhances the use of other DTs.	Adomavicius et al. (2004)
Hype Cycle	Development Stage	Technology Trigger: Potential technology breakthroughs and first proof-of-concepts. Peak of Inflated Expectations: Application limited to a few companies. Trough of Disillusionment: Fail of implementations, further investments into DT in doubt. Slope of Enlightenment: Roll out of second and third generation products. Plateau of Productivity: Mainstream adoption.	(Gartner Inc., 2009, 2010, 2011, 2012, 2013, 2014, 2015, 2016, 2017)
Device	Scope	Cyber: Acting focus in cyber domain. Synergic: No focus, support of interaction and affection of both domains. Physical: Acting focus in physical domain.	Broy et al. (2012); Horvath and Gerritsen (2012); Kagermann et al. (2013); Zamfirescu et al. (2014)
Inter-action	Multiplicity	One-to-one: Interaction between two entities. One-to-many: Connection of various entities, acting as a hub. Many-to-many: Interaction between multiple entities simultaneously.	Porter and Heppelmann (2014); Püschel et al. (2020); Oberländer et al. (2018)
	Direction	Uni-directional: Data flow in one direction. Bi-directional: Data flow in more than one direction.	Püschel et al. (2020); Oberländer et al. (2018); Suchman (2009)
Data	Data Treatment	Collection: Creation of new data. Aggregation: Aggregation of existing data Analysis: Interpretation of existing data on the basis of an underlying logic. Execution: Trigger of (data) activities on the basis of instructions or commands	Borgia (2014); Püschel et al. (2020); Miller and Mork (2013)
	Input	Digital: Digital form of data input. Physical: Physical form of data input. Visual: Visual form of data input. Acoustic: Acoustic form of data input.	Derived based on the reserachers' experience

	Output	Digital: Digital form of data output. Physical: Physical form of data output. Visual: Visual form of data output. Acoustic: Acoustic form of data output.	Derived based on the reserachers' experience
Service	Main Principle	Information Gathering: Gathering large amounts of data. Efficiency Enhancement: Transforming data into valuable knowledge. Customer Focus: Easing customer interaction. Ubiquity: Enabling location independent connectivity.	BarNir, Gallaugher, and Auger (2003), Iansitiy and Lakhani (2014), Pousttchi and Thurnher (2006)
	Domain	Cross-sectional: Applicable in various areas and for several purposes. Specific: Applicable for specific purpose.	Gerpott (2013)

Iteration 2

Step 3: To enhance the initial taxonomy, we decided to classify existing DTs and continued the development process by applying the empirical-to-conceptual approach. In line with Gregor (2006), Williams, Chatterjee, and Rossi (2008), Tsatsou, Elaluf-Calderwood, and Liebenau (2010), and F. von Briel and Schneider (2012), we tested the layers, dimensions, and characteristics of our taxonomy in subsequent iterations by classifying DTs and adjusting the taxonomy accordingly.

Step 4e: In line with Gregor (2006), Williams, Chatterjee, and Rossi (2008), Tsatsou, Elaluf-Calderwood, and Liebenau (2010), and F. von Briel and Schneider (2012), we tested the layers, dimensions, and characteristics of our taxonomy by classifying DTs and adjusting the taxonomy accordingly. To begin, we chose 46 DTs from the GHC from 2015 to 2017 (Gartner Inc., 2015, 2016, 2017). To evaluate the usefulness of the taxonomy, the sample was classified by two co-authors, working independently from one another.

Step 5e: Based on our sample, we identified the following DT characteristics:

- Aggregation of existing data from different data sources (data collection)
- Provision of data to support decision making and/or the actual process of decision (decision support & making)
- Capability of converting digital data into other forms (physical, visual, acoustic) or change of the digital depiction (data-to-X)
- Enabling of location independent connectivity and accessibility of information, objects, people, and activities
- Maximization of the result for a given input or minimization of the input for a given result. Variables are, inter alia, scalability, transmission rate, amount of data, or power rate (performance improvement)

For example, Smart Dust is focused on the aggregation and collection of data, while Cognitive Expert Advisors support decision making through big data approaches. 4D Printing converts digital data into physical products. 802.11ax connects devices via Wi-Fi. Neuromorphic Hardware raises computing power.

- DT in hype phase. Not frequently used (fashionable)
- DT is widely known and accepted. Frequently used (established)
- DT which did not establish itself or got replaced by other technology after hype phase (outdated)

For example, Volumetric Displays are still a vision and only few prototypes exist. Machine Learning is already established and widely used in different contexts. A popular example for an outdated DT is Public Virtual Worlds which couldn't be established.

- Use of the DT in business context

- Use of the DT in private context

- Use of the DT in business and private context

While Enterprise Taxonomy and Ontology Management is used in business, Connected Home has a focus on private households.

- DT transfers existing data. No modification of the content. (transmission)

For example, 802.11ax and other Wi-Fi networks only transfer data.
All listed characteristics were in line with the meta-characteristic as they represent DT characteristics.

Step 6e: We recognized that the characteristics data collection, decision support & making, data-to-X, connectivity, performance improvement describe the purpose of a DT more precisely than information gathering, efficiency enhancement, customer focus, and ubiquity of iteration 1. Thus, we replaced these characteristics:

- Dimension Main Principle: data collection, decision support & making, data-to-X, connectivity, performance improvement

In contrast, the recognized characteristics of the dimension Hype Cycle turned out to be to narrow, especially when considering a longer time period. Thus, we replaced the characteristics of Iteration 1 (technology trigger, peak of inflated expectations, trough of disillusionment, slope of enlightenment, plateau of productivity):

- Dimension Hype Cycle: fashionable, established, outdated

We identified a new dimension which focuses on the context in which a DT is used. Thus, we added the following dimension:

- Dimension Context: business, private, business & private

The remaining characteristics were additional characteristics to dimensions we identified previously. Thus, these dimensions became:

- Dimension Data Treatment: collection, aggregation, analysis, execution, transmission

The layer structure of Iteration 1 remained unchanged (High-level, Hype Cycle, Device, Interaction, Data, Service). The dimension context became part of the High level layer.

After revising the layers, dimensions, and characteristics, we received the following taxonomy:

T_2 = {*High level* [Role of Technology (Application, Component, Infrastructure),
Context (Business, Private, Business & Private],
Hype Cycle [Development Stage (Fashionable, Established, Outdated)],
Device [Scope (Cyber, Synergic, Physical)],
Interaction [Multiplicity (One-to-one, One-to-many, Many-to-many),
Direction (Uni-directional, Bi-directional)],
Data [Data Treatment (Collection, Aggregation, Analysis, Execution, Transmission), Input (Digital, Physical, Visual, Acoustic), Output (Digital, Physical, Visual, Acoustic)],
Service [Main Principle (data collection, decision support & making, data-to-X, connectivity, performance improvement), Domain (Cross-sectional, Specific)]}

Step 7: As we added some dimensions and characteristics, the taxonomy is still not concise due to a large number of layers, dimensions, and characteristics. Also the taxonomy was not comprehensive as not all real-life objects could be classified. As the revised taxonomy did not meet our subjective ending conditions, we conducted a third iteration.

Iteration 3

Step 3: Once again, we followed the *empirical-to-conceptual approach* to further develop the taxonomy in response to the classification of real-world objects, i.e., DTs, by two focus groups involving IS academics.

Step 4e: For this purpose, we asked the participants to classify a sample of ten DTs, which were selected to meet the following criteria: (1) at least two DTs for every characteristic had to be included, and (2) the sample had to be a proper subset of the 46 DTs used in the second iteration. To aid the classification, we shared instructions, including a detailed descriptions of the taxonomy and definitions of the selected DTs, as provided in the GHC. After all participants had completed the classifications, we discussed problems they had encountered and suggestions for improving the taxonomy in a joint workshop. Each focus group took 75 minutes and was hosted by two co-authors. The two focus groups were made up of eight and 20 participants from two different universities. The first focus group consisted of six doctoral students and two master's students, while the second group included three professors, twelve doctoral students, and five master's students. All participants shared an IS background with a focus on digitalization topics such as blockchain, smart factory, deep learning, smart things, big data, or augmented reality. After each focus group meeting, we analyzed the findings quantitatively (e.g. calculating hit ratios) and qualitatively and refined the taxonomy accordingly.

Step 5e: Based on our sample, the co-authors and focus groups challenged the following DT characteristics:

- fashionable
- established
- outdated

We recognized that these characteristics are time dependent. However, characteristics should be "transcendent of a particular moment" (Williams, Chatterjee, & Rossi, 2008).

- business
- private
- business & private

For almost every DT we were able to create a scenario in which it could be used in a private and business environment. In addition, these characteristics do not describe the inherent nature of DTs, but rather their application area.

- cross-sectional
- specific

Within the fast-moving field of digitalization, DTs are increasingly transferred to new application field, serving multiple purposes. Hence, these characteristics are time-bound.

- synergic
- physical

We recognized blurring boundaries between those two characteristics which complicate intuitive classification. Furthermore, DT always include some kind of cyber component by their nature. For example, we assigned a physical focus to autonomous vehicles, because they move and change their physical environment. However, one could argue that they process data and therefore have a synergetic focus.

- visual
- acoustic

The sample included various DTs, e.g., Augmented Reality, which may comprise several different inputs and outputs such as visual, acoustic, and physical. However, a clear assignment was not always possible.

- component

The characteristic component refers to the combination of existing technologies to form new kinds of technologies (Adomavicius et al., 2004) and applied to almost every examined DT. For example, all DTs which collect data are sensor-based. Therefore, this characteristic did not yield any useful information.

All listed characteristics were in line with the meta-characteristic as they represent DT characteristics.

Step 6e: Due to their time dependency, we decided to delete the dimensions Development Stage and Domain and their characteristics without substitution.

We deleted the Context dimension and its characteristics as they are highly dependent on the application area.

Due to a missing delimitation, we joined the characteristics synergic and physical towards cyber-physical. Hence, we received the following dimension:

- Dimension Scope: cyber, cyber-physical

Due to a lack of discriminatory power, we deleted the characteristics visual and acoustic. However, we extended the definition of the characteristic physical to include acoustic and visual input and output:

- Dimension Input / Output: digital, physical

Due to a lack of information gain, we deleted the characteristic component, forming the following dimension:

- Dimension Role of Technology: application, infrastructure

Due to the elimination of the dimensions Hype Cycle and Context as well as the shift of the Role of Technology dimension towards the Device Layer, we deleted the layers High level and Hype Cycle. Hence, we received the following layers: Device, Interaction, Data, Service.

After revising the layers, dimensions, and characteristics, we received the following taxonomy:

T_3 = {*Device* [Role of Technology (Application, Infrastructure), Scope (Cyber, Cyber-physical)],
Interaction [Multiplicity (One-to-one, One-to-many, Many-to-many), Direction (Uni-directional, Bi-directional)],
Data [Data Treatment (Collection, Aggregation, Analysis, Execution, Transmission), Input (Digital, Physical), Output (Digital, Physical)],
Service [Main Principle (data collection, decision support & making, data-to-X, connectivity, performance improvement)}

Step 7: The subjective ending conditions were not yet met as some participants were unable to classify DTs without the full range of information, and the taxonomy still comprised too many dimensions and characteristics. Having revised the taxonomy in response to the feedback from the focus groups, we conducted a fourth iteration.

Iteration 4

Step 3: Our main goal was to challenge the robustness of the taxonomy by considering more DTs. Hence, we applied the *empirical-to-conceptual approach.*

Step 4e: In order to evaluate if the taxonomy covers the great variety of DTs, we extended the considered timeframe to the GHCs of 2009 to 2017, resulting in a sample of 92 DTs.

Step 5e: Based on our sample, the co-authors challenged the following DT characteristics:

- data collection
- decision support & making

- data-to-X
- connectivity
- performance improvement

The 'main principle' reflects the idea of Arthur (2009) and Ferré (1988), after which every technology serves distinct purposes. A purpose-oriented view is suitable for distinguishing DTs, as it complements the rather technical view on technologies. When classifying DTs, however, we recognized that a DT's characteristics for the main principle dimension are a good indicator for its characteristics related to the other dimensions.

Based on our sample, we identified the following DT characteristics:

- active usage of a DT by humans
- passive usage of a DT by humans

All listed characteristics were in line with the meta-characteristic as they represent DT characteristics.

Step 6e: Due to relations to other characteristics, we abandon the dimension Main Principle, but strived for higher-level insights by means of purpose-related archetypes.

We identified a new dimension which focuses on the use of a DT. Thus, we added the following dimension:

- Dimension Human Involvement: active usage, passive usage

After reviewing the existing layers, we recognized similarities with regard to the layered architecture of Yoo et al. (2010). Whereas the layers service and device already existed within our taxonomy, the terms data and content as well interaction and network could be used interchangeably within our context. Hence, we decided to align our dimensions along the established architecture of Yoo et al. (2010), i.e., device, network, content, service .

After revising the layers, dimensions, and characteristics, we received the following taxonomy:

T_4 = {*Device* [Role of Technology (Application, Infrastructure), Scope (Cyber, Cyber-physical)],
Network [Multiplicity (One-to-one, One-to-many, Many-to-many), Direction (Uni-directional, Bi-directional)],
Content [Data Treatment (Collection, Aggregation, Analysis, Execution, Transmission), Input (Digital, Physical), Output (Digital, Physical)],
Service [Human Involvement (Active Usage, Passive Usage)}

Step 7: The classification of these DTs only required minor changes to the taxonomy, e.g. the wording of single characteristics. The minimal adjustment needed in the fourth iteration reflected the increasing stability of the taxonomy. However, the ending condition of 'no further modification' was still not met. Hence, we conducted a fifth iteration.

Iteration 5

Step 3: With only marginal changes during the previous iteration, we again adopted the *empirical-to-conceptual approach*.

Step 4e: To confirm the stable results of iteration 4, we repeated the classification with the same sample of 92 DTs from the GHC (2009 to 2017) as in iteration 4.

Step 5e: Based on our sample, we did not identify new layers, dimensions, or characteristics.

Step 6e: No changes to the taxonomy. Hence, the final version of the taxonomy is as follows: T_5 = {*Device* [Role of Technology (Application, Infrastructure), Scope (Cyber, Cyber-physical)],
Network [Multiplicity (One-to-one, One-to-many, Many-to-many), Direction (Uni-directional, Bi-directional)],
Content [Data Treatment (Collection, Aggregation, Analysis, Execution, Transmission), Input (Digital, Physical), Output (Digital, Physical)],
Service [Human Involvement (Active Usage, Passive Usage)}

Step 7: As no modifications were needed within this iteration, we agreed that the taxonomy now met the fourth objective ending condition. As all objective ending conditions had been met and the co-authors agreed that the taxonomy was concise, robust, comprehensive, extendible, and explanatory (Nickerson et al., 2013), we decided to refrain from another iteration and to consider the current version of the taxonomy as final. This version also served as a foundation for the derivation of purpose-related DT archetypes.

Appendix D: Details on Encoding and Measures to Decide on Cluster Solution

As the meaningfulness of clustering results is dependent on the input data (Morrison, 1967) we strived for comparability among our input variables. All dimensions of our taxonomy are nominally scaled and either mutually exclusive or non-exclusive. As a distance measure, we chose the Manhattan-metric, an established approach which can deal with nominally scaled dimensions, has proven useful in combination with the Ward algorithm (Strauss & Maltitz, 2017), and has been applied in many other cases (e.g., N. C. M. Ross & Wolfram, 2000; Romero, González, Martín, Vázquez, & Ortiz, 2015). We organized the classification of DTs such that every characteristic is represented by a separate column and assigned 1, if the characteristic is observable, and 0 otherwise (H. Gimpel, Rau, & Röglinger, 2018). We then standardized the maximum possible distance for each dimension to 1 to ensure an equal weighting of all dimensions. While 'mutually exclusive' dimensions already fulfilled this requirement, we modified all 'non-exclusive' dimensions as follows: for dimensions with two characteristics, we multiplied the assigned binary variable by 0.5 (Bacher, Pöge, & Wenzig, 2010). Due to the lack of a common approach in the literature, we then transferred this procedure to 'non-exclusive' dimensions with more than two characteristics. We therefore multiplied binary variables with the reciprocal of the number of characteristics per dimension, e.g., 0.2 for dimensions with five characteristics, again ensuring a maximum possible distance of 1 within the respective dimension. For example, for the non-exclusive dimension of 'data treatment', all five characteristics receive a value of either 0, or 0.2, so that the maximum cumulated distance within the dimension is maximum 1. The exclusive dimension of 'human involvement', in turn, assigns 0 or 1 to its two characteristics. Again, the cumulated distance within the dimension is maximum 1, as mutual exclusivity demands that 1 is assigned to exactly one characteristic.

To conclude the cluster analysis, we determined the ideal number of clusters. Table D1 lists the twelve clustering validation indices we considered in order to calculate the appropriate number of clusters when deriving purpose-related archetypes. In accordance with our data set and the Ward algorithm, we calculated clustering validation indices for hard (i.e. every object is part of exactly one cluster) and internal (i.e., information is only used if it is also needed to conduct the cluster analysis) clustering. We also used optimization-like (i.e. maximum or minimum value, smallest number of clusters such that the index is closest to a significance or critical value) and difference-like (i.e. maximum difference between hierarchy levels) validity indices (Vendramin et al., 2010). To select the optimal number of clusters, the indices consider either compactness (i.e. intracluster homogenity), separation (i.e. intercluster isolation), or both (Halkidi, Vazirgiannis, & Batistakis, 2000). We discuss the values of these clustering validation indices in the manuscript.

				Type of Optimization		Measure	
Reference	Index	Optimal Number of Clusters	Value	Optimization	Difference	Compactness	Separation
Ball and Hall (1965)	Ball-Hall Index	3	281.4		x	x	
Beale (1969)	Beale Index	9	-41.1	x		x	x
Calinski and Harabasz (1974)	Calinski-Harabasz (CH) Index	15	2,879.9	x		x	x
Davies and Bouldin (1979)	Davies-Bouldin (DB) Index	13	0.5	x		x	x
Duda and Hart (1973)	Duda Index	9	14.7	x		x	x
Duda and Hart (1973)	Pseudot2 Index	9	-38.4	x		x	x
Dunn (1974)	Dunn Index	6	0.6	x		x	x
Halkidi et al. (2000)	SD Index	6	18.5	x		x	x
Hartigan (1975)	Hartigan Index	5	182.3		x	x	x
Hubert and Levin (1976)	C Index	12	0.2	x		x	
Krzanowski and Lai (1988)	Krzanowski-Lai Index	2	29.0	x		x	

McClain and Rao (1975)	McClain-Rao Index	2	0.2	x		x	x
Milligan (1980, 1981)	Point-biserial Correlation Coefficient	2	0.8	x		x	x
Ratkowsky and Lance (1978)	Ratkowsky-Lance Index	2	0.4	x			x
Rohlf (1974)	Tau Index	9	14,171.2	x		x	x
Rousseeuw (1987)	Silhouette Index	14	0.8	x		x	x

				Type of Optimization		Measure	
Reference	**Index**	**Optimal Number of Clusters**	**Value**	**Optimization**	**Difference**	**Compactness**	**Separation**
Ball and Hall (1965)	Ball-Hall Index	3	281.4		x	x	
Beale (1969)	Beale Index	9	-41.1	x		x	x
Calinski and Harabasz (1974)	Calinski-Harabasz (CH) Index	15	2,879.9	x		x	x
Davies and Bouldin (1979)	Davies-Bouldin (DB) Index	13	0.5	x		x	x
Duda and Hart (1973)	Duda Index	9	14.7	x		x	x
Duda and Hart (1973)	Pseudot2 Index	9	-38.4	x		x	x
Dunn (1974)	Dunn Index	6	0.6	x		x	x
Halkidi et al. (2000)	SD Index	6	18.5	x		x	x
Hartigan (1975)	Hartigan Index	5	182.3		x	x	x
Hubert and Levin (1976)	C Index	12	0.2	x		x	
Krzanowski and Lai (1988)	Krzanowski-Lai Index	2	29.0	x		x	
McClain and Rao (1975)	McClain-Rao Index	2	0.2	x		x	x
Milligan (1980, 1981)	Point-biserial Correlation Coefficient	2	0.8	x		x	x
Ratkowsky and Lance (1978)	Ratkowsky-Lance Index	2	0.4	x			x
Rohlf (1974)	Tau Index	9	14,171.2	x		x	x
Rousseeuw (1987)	Silhouette Index	14	0.8	x		x	x

Appendix E: Classification Results (Taxonomy)

Table E1 gives an overview of the 92 DTs included in our sample and their classification in terms of characteristics and purpose-related archetype. The given numbers in the first column refer to the numbers in Appendix A.

Table E1. Details on the Classification of 92 Digital Technologies

		Device				Network					Content									Service		
		Role of Technology		Scope		Multiplicity			Direction		Data Treatment					Input		Output		Human Involvement		
No.*	Technology	Application	Infrastructure	Cyber	Cyber-physical	One-to-One	One-to-Many	Many-to-Many	Uni-directional	Bi-directional	Collection	Aggregation	Analysis	Execution	Transmission	Digital	Physical	Digital	Physical	Active Usage	Passive Usage	Purpose-related DT Groups
1	3D Bioprinting Systems for Organ Transplant / 3D Bioprinting Systems / 3D Prioprinting	x			x	x			x					x		x			x	x		Actor-based Data Execution
2	3D Flat-Panel TVs and Displays / 3D Flat-Panel Displays	x			x	x			x						x	x			x	x		Actor-based Data Execution
3	3D Printing	x			x	x			x					x		x			x	x		Actor-based Data Execution
4	3D Scanners	x			x	x			x		x	x			x		x	x		x		Sensor-based Data Collection
5	4D Printing	x			x	x			x					x		x			x	x		Actor-based Data Execution
6	4G Standard		x	x				x		x					x	x		x			x	Connectivity & Computation
7	5G		x	x				x		x					x	x		x			x	Connectivity & Computation
8	802.11ax		x	x				x		x					x	x		x			x	Connectivity & Computation
9	Activity Streams	x		x		x				x		x			x	x		x		x		Analytical Insight Generation
10	Advanced Analytics with Self-Service Delivery	x			x	x				x	x		x		x	x		x	x	x		Augmented Interaction
11	Affective Computing	x			x	x				x	x		x				x	x		x		Natural Interaction
12	Application Stores/Mobile Application Stores		x	x			x			x					x	x		x		x		Platform Provision
14	Augmented Data Discovery / Smart Data Discovery	x			x	x				x		x	x		x	x	x	x	x	x		Augmented Interaction
15	Augmented Reality	x			x	x				x					x	x			x	x		Augmented Interaction
16	Automatic Content Recognition	x			x	x				x	x		x			x	x	x		x		Natural Interaction
17	Autonomous Field Vehicles	x			x		x			x	x		x	x	x	x	x	x	x	x		Self-dependent Material Agency
18	Autonomous Vehicles	x			x		x			x	x		x	x	x	x	x	x	x	x		Self-dependent Material Agency
21	Bioacoustic Sensing	x			x	x			x		x	x	x				x		x	x		Sensor-based Data Collection
22	Biochips	x			x	x			x		x		x				x	x		x		Sensor-based Data Collection
23	Biometric Authentication Methods	x			x	x			x		x		x				x	x		x		Sensor-based Data Collection
24	Blockchain		x	x				x		x					x	x		x			x	Connectivity & Computation
25	Brain Computer Interface / Computer-Brain Interface	x			x	x			x		x		x				x	x		x		Sensor-based Data Collection
26	Broadband over Power Lines		x	x				x		x					x	x		x			x	Connectivity & Computation
28	Citizen Data Science	x		x		x				x		x	x		x	x		x		x		Analytical Insight Generation
29	Cloud/Web Platforms		x	x			x			x					x	x		x		x		Platform Provision
32	Cognitive Expert Advisors	x			x	x				x			x			x	x	x	x	x		Augmented Interaction
33	Complex Event Processing	x		x		x				x		x	x			x		x		x		Analytical Insight Generation
34	Commerical UAVs (Drones)	x			x	x				x	x		x	x	x	x	x	x		x		Natural Interaction
36	Consumer 3D Printing	x			x	x			x					x		x			x	x		Actor-based Data Execution
41	Context-enriched Services	x		x		x				x			x		x	x		x		x		Analytical Insight Generation
44	Conversational User Interfaces	x			x	x				x	x				x		x		x	x		Natural Interaction
46	Cryptocurrencies		x	x				x		x					x	x		x		x		Platform Provision
47	Cryptocurrency Exchange		x	x			x			x					x	x		x		x		Platform Provision
49	Data Broker PaaS		x	x			x			x		x	x		x	x		x		x		Platform Provision
51	Deep learning	x		x		x				x	x		x			x		x		x		Analytical Insight Generation
52	Deep Reinforcement Learning	x		x		x				x	x		x			x		x		x		Analytical Insight Generation
55	Digital Twin	x			x	x				x	x				x	x	x	x		x		Natural Interaction
56	E-Book Readers		x		x	x				x	x				x	x	x		x	x		Personal Mobile Communication
57	Edge Computing		x	x				x		x	x		x		x	x		x			x	Connectivity & Computation
58	Electronic Paper	x			x	x				x					x	x	x		x	x		Augmented Interaction
60	Enterprise 3D Printing	x			x	x			x					x		x			x	x		Actor-based Data Execution
61	Enterprise Taxonomy and Ontology Management	x		x		x			x			x				x		x		x		Analytical Insight Generation
64	Gesture Control Device/Gesture Control	x			x	x				x	x		x		x		x	x		x		Natural Interaction
65	Gesture Regocnition	x			x	x			x		x				x		x	x		x		Sensor-based Data Collection
69	Hosted Virtual Desktops		x	x				x		x					x	x		x			x	Connectivity & Computation
72	Hybrid Cloud Computing		x	x			x			x					x	x		x		x		Platform Provision
74	Image Recognition	x			x	x				x	x		x		x		x	x		x		Natural Interaction
75	In-memory Analytics	x		x		x				x		x	x			x		x		x		Analytical Insight Generation
76	In-memory Database Management Systems	x		x		x				x		x				x		x		x		Analytical Insight Generation
77	Interactive TV	x			x	x				x	x		x		x	x			x	x		Augmented Interaction
79	Internet TV	x			x	x				x					x	x			x	x		Augmented Interaction
80	IoT		x		x			x		x					x	x	x	x	x		x	Connectivity & Computation
81	IoT Platform		x	x			x			x			x		x	x		x		x		Platform Provision
82	Location Intelligence/Location-Aware Applications	x			x	x				x	x		x				x	x		x		Natural Interaction
83	Machine-to-Machine Communication Services		x	x				x		x					x	x		x			x	Connectivity & Computation
84	Machine Learning	x		x		x				x	x		x			x		x		x		Analytical Insight Generation
85	Media Tablets		x		x	x				x	x				x	x	x	x	x	x		Personal Mobile Communication
86	Mesh Networks: Sensor	x			x	x			x		x				x		x	x		x		Sensor-based Data Collection
90	Mobile OTA Payment / Over-the-Air Mobile Phone Payment Systems, Developed Markets	x		x		x				x			x		x	x		x		x		Analytical Insight Generation
93	Natural-Language Question Answering	x			x	x				x	x		x		x		x		x	x		Natural Interaction
95	Neuromorphic Hardware		x	x				x		x					x	x		x			x	Connectivity & Computation
96	NFC (Near Field Communication)		x	x				x		x					x	x		x			x	Connectivity & Computation
97	NFC Payment	x		x		x				x			x		x	x		x		x		Analytical Insight Generation
98	Online Video		x	x			x			x		x			x	x		x		x		Platform Provision
99	Pen-Centric Tablet PCs		x		x	x				x	x				x	x	x	x	x	x		Personal Mobile Communication
100	People-Literate Technology	x			x	x				x	x		x		x		x		x	x		Natural Interaction
105	Public Virtual / Worlds Virtual Worlds		x	x				x		x					x	x		x		x		Connectivity & Computation
107	Quantum Computing		x	x				x		x					x	x		x			x	Connectivity & Computation
108	QR/Color Code	x			x	x			x					x			x	x		x		Sensor-based Data Collection
110	Serverless PaaS		x	x			x			x					x	x		x		x		Platform Provision
112	Smart Advisors	x			x	x				x	x		x		x	x	x	x	x	x		Augmented Interaction
113	Smart Dust	x			x	x			x		x				x		x	x		x		Sensor-based Data Collection
116	SOA		x	x				x		x					x	x		x			x	Connectivity & Computation
117	Social Analytics / Social Network Analysis	x		x		x				x	x		x			x		x		x		Analytical Insight Generation
119	Social TV	x			x	x				x					x	x		x	x	x		Augmented Interaction
122	Speech Analytics/Audio Mining	x			x	x			x		x		x	x			x	x	x	x		Sensor-based Data Collection
123	Speech-to-speech Translation	x			x	x				x	x		x		x		x		x	x		Natural Interaction
124	Speech Recognition	x			x	x				x	x		x	x	x		x	x	x	x		Natural Interaction
125	Surface Computers		x		x	x				x	x				x	x	x	x	x	x		Personal Mobile Communication
126	Tablet PC		x		x	x				x	x				x	x	x	x	x	x		Personal Mobile Communication
127	Tangible User Interfaces	x			x	x				x	x		x		x		x	x	x	x		Natural Interaction
128	Terahertz Waves		x	x				x		x					x	x		x			x	Connectivity & Computation
129	Text Analytics	x		x		x				x		x	x			x		x		x		Analytical Insight Generation
130	Video Analytics for Customer Service	x			x	x			x		x		x			x	x	x		x		Sensor-based Data Collection
131	Video Search	x		x		x				x			x			x		x		x		Analytical Insight Generation
132	Video Telepresence	x			x	x				x	x				x		x	x	x	x		Natural Interaction
133	Virtual Assistants	x			x	x				x	x	x	x		x	x		x	x	x		Augmented Interaction
134	Virtual Personal Assistant	x			x	x				x	x	x	x		x	x		x	x	x		Augmented Interaction
135	Virtual Reality	x			x	x				x	x				x	x			x	x		Augmented Interaction
136	Volumetric Displays / Volumetric and Holumetric Displays	x			x	x				x	x				x		x		x	x		Natural Interaction
137	Wearables / Wearable User Interfaces	x			x	x				x	x				x		x	x		x		Natural Interaction
139	Wikis	x		x		x				x		x				x		x		x		Analytical Insight Generation

* refers to the number in Appendix A1

Appendix F: Absolute and Relative Hit Ratios

Our classification results revealed initial insights regarding the taxonomy's dimensions and characteristics. Figure F1 shows an overview of relative and absolute ratios. Starting with the service layer, we found that humans actively use the capabilities of DTs in 84% of all cases examined. This finding complies with the trend toward interaction and communication technologies such as NLQA (Bouziane, Bouchiha, Doumi, & Malki, 2015), which increasingly merge the physical with the digital world. A minority of DTs are hidden from users, yet network structures and hardware – e.g. 802.11ax – can support a large number of devices or applications. Regarding the content layer, data 'aggregation' always appears in combination with the comparatively frequent activities data 'analysis' (45%) and data 'transmission' (68%). The same holds for data 'collection', which occurs in 48% of all cases, but never as a single activity within this dimension. Regarding input and output, 42% of the DTs under investigation feature both 'digital' input and output, mainly including wireless networks and infrastructures technologies. Further, only 7% feature 'physical' input and output, e.g. NLQA. The remaining 51% feature hybrid forms of receiving and providing 'digital' and 'physical' data. In the network layer, 78% of the examined DTs enable 'bi-directional' interaction among the involved entities, which is another indicator of increased connectivity and use of HMIs. In terms of the multiplicity dimension, our sample highlights the fact that only 12% of the DTs we investigated participate in 'one-to-many' and only 10% in 'many-to-many' interactions. Again, platform and connectivity technologies connect multiple objects. The most common interaction pattern is to be found in a 'one-to-one' (78%) connection. Further, our assessment of the device layer revealed that 67% of the classified DTs are application-oriented. This high percentage accounts for the increasing dissemination and modularization of services, with DTs no longer tied to the use one specific hardware or device. Further, over half the DTs in our sample have a 'cyber-physical' focus (58%). The use and further development of sensor, actor, and HMI technology might be a possible explanation for this. All in all, we observed a high number of interaction and communication features, which are, for the most part, realized through device-independent services with a focus on 'bi-directional' interaction with humans.

Layer	Dimension	Characteristic				
Device	Role of Technology	Application (67%)	Infrastructure (33%)			
	Scope	Cyber (42%)	Cyber-Physical (58%)			
Network	Multiplicity	One-to-One (78%)	One-to-Many (12%)	Many-to-Many (10%)		
	Direction	Uni-directional (22%)	Bi-directional (78%)			
Content	Data Treatment	Collection (48%) [25%]	Aggregation (16%) [9%]	Analysis (45%) [24%]	Execution (12%) [6%]	Transmission (68%) [36%]
	Input	Digital (75%) [65%]	Physical (40%) [35%]			
	Output	Digital (78%) [67%]	Physical (39%) [33%]			
Service	Human Involvement	Active Usage (84%)	Passive Usage (16%)			

(...): absolute ratio [...]: relative ratio

Figure F1. Classification Results of 92 Digital Technologies

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