TOWARDS A TAXONOMY OF DIGITAL TWIN APPLICATIONS FOR TELEMEDICAL HEALTHCARE

Eileen Doctor
Fraunhofer FIT, eileen.doctor@uni-bayreuth.de

Christian Keweloh
Project Group Business & Information Systems Engineering of the Fraunhofer FIT, c_keweloh@web.de

Christoph Buck
Queensland University of Technology, christoph.buck@qut.edu.au

Torsten Eymann
University of Bayreuth, torsten.eymann@uni-bayreuth.de

Follow this and additional works at: https://aisel.aisnet.org/ecis2021_rip

Recommended Citation
Doctor, Eileen; Keweloh, Christian; Buck, Christoph; and Eymann, Torsten, "TOWARDS A TAXONOMY OF DIGITAL TWIN APPLICATIONS FOR TELEMEDICAL HEALTHCARE" (2021). ECIS 2021 Research-in-Progress Papers. 12.
https://aisel.aisnet.org/ecis2021_rip/12

This material is brought to you by the ECIS 2021 Proceedings at AIS Electronic Library (AISeL). It has been accepted for inclusion in ECIS 2021 Research-in-Progress Papers by an authorized administrator of AIS Electronic Library (AISeL). For more information, please contact elibrary@aisnet.org.
TOWARDS A TAXONOMY OF DIGITAL TWIN APPLICATIONS FOR TELEMEDICAL HEALTHCARE

Research in Progress

Eileen Doctor, Project Group Business & Information Systems Engineering of the Fraunhofer FIT, eileen.doctor@fit.fraunhofer.de

Christian Keweloh, FIM Research Center, University of Bayreuth, Project Group Business & Information Systems Engineering of the Fraunhofer FIT, Bayreuth, Germany, christian.keweloh@fim-rc.de

Christoph Buck, School of Management, Queensland University of Technology, Brisbane, Australia, christoph.buck@qut.edu.au

Torsten Eymann, FIM Research Center, University of Bayreuth, Project Group Business & Information Systems Engineering of the Fraunhofer FIT, Bayreuth, Germany, torsten.eymann@uni-bayreuth.de

Abstract

The industrial paradigm of a Digital Twin (DT), a virtual representation of a physical object, promises an impactful opportunity to advance digital healthcare. Especially in telemedicine, the application of DTs could yield various benefits for patients, providers, and payers. However, the development of DTs for healthcare and specifically telemedicine is not yet mature. Therefore, this research in progress paper attempts to structure the research field and classify DTs for digital health and in future, for telemedicine. Based on a systematic literature review (SLR) and grounded theory analysis techniques, we derive 12 dimensions and 35 characteristics that support researchers and practitioners to develop, apply, refine and evaluate various DT applications. The taxonomy serves as a promising starting point for further research on implementing or adopting DTs in healthcare and telemedicine. An application of a real-world objective already shows the feasibility of our taxonomy.

Keywords: Digital Twin, Digital Health, Telemedicine, Taxonomy.

1 Introduction

The debate on telemedicine as the future of healthcare provision has persisted for years, as telemedical care offers numerous opportunities for patients, providers, and payers (Darkins et al., 2008). When applied, telemedicine can prevent or fill the impending or existing gap in healthcare (Ekeland et al., 2010), especially in rural areas (Gröne and Garcia-Barbero, 2001). For instance, increased demand for medical care can be met by telemedical interventions that enhance access to services (Hjelm, 2005). These telemedical interventions tend to focus on patients and their environment (Ekeland et al., 2010). However, the medical and personal information required for this is a significant obstacle. Only through comprehensive and up-to-date patient data and the ubiquitous access by those involved in the healthcare process, more efficient and effective treatment could be achieved and benefits realized (Dittmar et al., 2009). Telemedicine promises an increase of equitable access to health information by improving its exchange throughout the entire healthcare process (Hjelm, 2005). An example of a widespread tool regarding patient data provision is the electronic health record (EHR). Although widespread, due to problems with inaccurate, subjective, or missing data in the patient records, the much needed equitable
access is not provided with an EHR (Holmes et al., 2012). Hence, the quality of the medical information, as well as the availability, completeness and actuality, must be ensured and call for innovative digital support (Brauns and Loos, 2015).

In contrast to the EHR, the Digital Twin (DT) technology represents a more holistic approach that incorporates individual patient data. In an industrial context, the application of DTs already addresses similar challenges as in telemedicine (Kritzinger et al., 2018; Tao et al., 2019), such as real-time data acquisition and synchronization, decision support, or workflow execution, to name a few. Consequently, this industrial paradigm of a DT creates impactful opportunities to improve telemedical care when adapted and applied accordingly, e.g., in terms of analytical assessment, predictive diagnosis and outcome optimization (Bruynseels et al., 2018). According to Enders and Hößbach (2019), a DT is a virtual representation of a physical object. When applied to healthcare, DTs virtually display a person or a patient and dynamically reflect information, including vital signs, molecular status, or lifestyle data (Bruynseels et al., 2018). Hence, DTs could be able to guarantee the availability and completeness of healthcare information. However, the approach is confronted with the sheer complexity of the human body. In contrast to industrial DTs, data for patients’ medical DTs are significantly more elusive and challenging to obtain holistically. Nevertheless, even DTs specific to a single disease or therapy are already showing effectiveness (Bruynseels et al., 2018). For example, a DT reduced the risk of false diagnoses (Rivera et al., 2019), or supported medical professionals in deciding for or against a treatment method (Björnsson et al., 2019).

The adaptation and application of DTs to healthcare offers great potential to provide the medical and personal information required for a widespread application of telemedical care. However, due to the novelty and varying understanding of DTs applied in healthcare (Enders and Hößbach, 2019), this paper aims to classify DTs for the healthcare sector. This classification of existing DT applications can identify best practices, reveal research gaps, or provide a standard definition and composition of successful DTs, for example. This will provide the basis for the specific application to telemedicine. Accordingly, this research in progress paper examines the following research question:

**How can Digital Twins be classified for digital health in general, and precisely, for telemedical applications?**

To answer the research question, a purposeful and viable taxonomy, according to Nickerson et al. (2013), is developed. The taxonomy structures the research field of DTs in healthcare and thereby enhances transparency in this comparably young field, which lacks theoretical insights (Gregor, 2006). The paper aims to compile all relevant dimensions and characteristics of DTs in healthcare. Therefore, the paper is structured as follows. In the first section, the theoretical background and related academic work are described. Subsequently, the taxonomy development process is introduced, including meta-characteristics, ending conditions, and the first iteration, which contains a systematic literature review (SLR) according to Okoli and Schabram (2010). In the third section, the preliminary results are compiled, followed by the discussion segment. In the last section, a conclusion is drawn, and future research is highlighted.

## 2 Conceptual Background

The initial form of a DT originated in the aerospace industry with NASA’s Apollo project in the late 1960s as a physical, computer-aided replica of a vehicle (Glaessgen and Stargel, 2012; Gries and Vickers, 2017). In 2003, Gries introduced the concept of a digital representation of a physical product (Gries, 2014), which was deemed to be the origin of DT (Tao et al., 2019). Gries (2003) defines a DT by three main components: Physical products in real space, virtual products in virtual space, and the connections of data that link the virtual and real-world. According to Liu et al. (2019), DTs have three characteristics: real-time reflection, interaction and convergence, and evolution and iteration. DTs can represent physical objects in real-time, monitor the entire lifecycle, and evolve accordingly. Moreover, DTs can optimize the physical counterpart based on an iterative virtual model (Liu et al., 2019). The research field is relatively new, and there exist various understandings of DTs (Kritzinger et al., 2018),
with no unambiguous definition of the concept in the scientific community (Negri et al., 2017). According to Enders and Hoßbach (2019), the smallest common denominator of all definitions is the idea of a DT as a virtual representation of a physical object. Thereby, the DT can be connected to the physical twin. A DT can be considered optimal and complete if it can provide all information derivable from the physical twin (Grieves and Vickers, 2017; Kritzinger et al., 2018). By analysis or simulation, a DT could even contain more information than the physical object itself can provide (Enders and Hoßbach, 2019).

DTs were relatively sparse at first but have become increasingly comprehensive and robust over the years. While a DT was initially merely descriptive, it has become progressively practical (Grieves and Vickers, 2017). According to Gartner’s Hype Cycle for Emerging Technologies, the DT technology remains highly promising, particularly in the application on individual persons (Panetta, 2020). Nowadays, the DT is applied in aerospace, industry 4.0, or customer services. Besides, an emerging field of application for DTs is healthcare. In accordance with the general interpretation of DTs by Enders and Hoßbach (2019), this paper focuses on the virtual representation of a person, respectively a patient. More specifically, this paper follows the definition of Bruynseels et al. (2018), who adapted the industrial concept of a DT to the healthcare sector and define DTs as virtual representations of an individual, which can dynamically reflect the molecular status, physiological state or lifestyle over time. Thereby, DTs could be able to guarantee the availability and completeness of healthcare information. Despite this, current health-related DTs cannot represent patients holistically due to their current evolutionary stage and lack of maturity. Nevertheless, even DTs that only partially mirror a patient regarding specific aspects of a disease or body system are already showing effectiveness (Bruynseels et al., 2018). For example, Fenz and Dirmberger (2011) improve intracranial aneurysm diagnosis through patient-specific blood flow simulation. Hirschvogel et al. (2019) predict healthy and pathological ventricular function or evaluate positive effects of a ventricular assist device concept based on a personalized functional DT of the heart. Additionally, the application of DTs can achieve and enable the benefits of telemedical care. Telemedical interventions, for instance, improve healthcare provision, reduce costs and enhance the quality of care (Driessen et al., 2018). In precision medicine, Feng (2018) already prevented medications’ undesirable side effects by leveraging DTs, thereby improving healthcare provision and reducing medical costs. Improved access to information for medical professionals and patients represents telemedicine’s added value (Hjelm, 2005). The application of a DT and the associated representation of relevant information can contribute to achieving and enhancing this benefit. Accordingly, the DT developed by Feng (2018) already enabled medical professionals without significant experience or expertise to develop a treatment plan, as all necessary information was available, and the most suitable options were predetermined.

3 Methodology

To answer the research question, we developed a classification scheme in the form of a taxonomy, according to Nickerson et al. (2013), as this approach is based on substantial literature and considered the established approach in the Information Systems discipline. The aim is to develop a taxonomy with a set of dimensions, each consisting of a set of characteristics that sufficiently describes DTs in digital health. Initially, a meta-characteristic is identified in line with the taxonomy's intention: Structuring characteristics of DTs in the context of digital health. Next, conditions that end the process need to be determined. A valuable taxonomy is characterized by the following subjective features: concise, robust, comprehensive, extensible, and explanatory. This paper focuses on all five subjective-, and three objective ending conditions during taxonomy development. Following this, the process begins with either an empirical or conceptual approach. The choice of which approach is chosen depends on the availability of data and the researcher’s knowledge of the area of interest. The taxonomy is considered complete if, in addition to all subjective criteria, the conditions “no new dimensions or characteristics were added in the last iteration”, “every dimension is unique and not repeated”, and “every characteristic is unique within its dimension” are fulfilled (Nickerson et al., 2013, p. 9).
Considering that DTs represent an immature research field, especially in healthcare, the first iteration follows the conceptual-to-empirical approach (Nickerson et al., 2013). Therefore, a SLR based on Okoli and Schabram (2010) and Moher et al. (2009) was conducted. In consideration of the research question, a search string was designed for the selection of relevant literature. The keywords were initially chosen generically, and by means of a thorough screening process, we manually focussed on healthcare. With this approach, we made sure not to exclude valuable papers and information. The following seven keywords were selected: ("digital twin" OR "digital avatar" OR "digital shadow" OR "virtual represent" OR "digital represent" OR "digital replic" OR "virtual replic"). To cover a broad academic spectrum, an abstract / title / keyword search was conducted in the eight databases PubMed, Medline, Web of Science, Science Direct, EBSCO, IEEE, AISeL, and ACMdL.

The initial result corresponded to 3954 papers, which were narrowed down by applying the following three exclusion criteria. 1316 papers were excluded by removing duplicates (n=661), non-academic articles (n=523), and non-English publications (n=323). The remaining 2638 articles were screened by title, abstract, and keywords, focusing on three additional exclusion criteria. Based on the first criterion, we checked the articles' relevance with respect to our research question and meta-characteristics. Depending on whether the presented research results are directly related to healthcare, we excluded articles using the second criterion. Finally, we applied the third exclusion criterion to analyze in detail why and how people are represented digitally. We conducted the screening process in three phases resulting in 2586 articles being excluded for further analysis. The remaining pool of 52 papers was defined and subjected to full-text analysis.

For this, the method of a SLR was extended by applying techniques of grounded theory analysis based on Corbin and Strauss (1990) and adapted by Wolfswinkel et al. (2013). We started this process with an initial screening of the identified articles, which enabled us to exclude 21 articles due to irrelevance or inconsistencies in the exclusion criteria. Based on the remaining 30 articles, we followed with forward and backward searching (Webster and Watson, 2002). Backward searching resulted in two relevant studies, while forward searching identified no additional articles. The final pool comprises 32 articles, which were further analyzed according to the three-step approach of Wolfswinkel et al. (2013). In a first step, the articles were screened, and text passages were broken down into separate units of meaning. All text passages that appear relevant to the meta-characteristics or research question were paraphrased, and thus, defined as open codes (Wolfswinkel et al., 2013). This process continued until the articles' renewed screening did not reveal any new open codes (Moghaddam, 2006). Overall, 482 open codes were identified and labeled accordingly. Subsequently, during the axial coding, these codes were consolidated and reduced by grouping codes with similar meanings (Wolfswinkel et al., 2013), resulting in 19 categories with 84 subcategories. The concluding selective coding links these categories with the meta-characteristic and the research question. Dimensions with respective characteristics were identified, consolidated, and interconnected based on the axial coding. The axial coding and the selective coding were performed in five iterations until no further consolidation appeared helpful.

4 Preliminary Results

The coding and analysis of the final pool of academic contributions resulted in a total of 12 dimensions to categorize a DT within a digital healthcare context: Representation, Procedure, Disease, User, Individuality, Subdivision, Data, Data-Acquisition, Data-Security, Activity-Level, DT-Modeling, Technology. These dimensions, with their respective characteristics, are depicted in Table 1 and described below.
The first dimension Representation categorizes, which aspects of the human body are digitally represented by the DT. The subordinate characteristics describe the eleven human body systems as a possible classification. Five articles examine the digital representation of a heart, and thus, the possibility to digitize a Cardiovascular System. Feng (2018) tried to depict the patient’s lungs (Respiratory System), Lauzeral et al. (2019), the liver (Renal System), or Pizzolato et al. (2019), the human neuromusculoskeletal system (Muscular or Skeletal System). For the three characteristics Nervous System, Immune or Endocrine System, and Exocrine or Excretory System, the SLR could not identify articles with matching examples. However, these body systems were added for completeness (Zhang, 2000) and the possible inclusion of future research. The dimension Procedure refers to the medical process during which the DT is applied or influenced by the DT. This covers the four characteristics of Prevention, Diagnosis, Treatment, and Rehabilitation. For instance, Chakshu et al. (2019) diagnosed stenosis in patients using a DT, and Goodwin et al. (2020) developed a DT that supports diabetes treatment by providing an optimized insulin injection strategy. Further, Mann (2020) evaluated a virtual avatar concerning neurorehabilitation. In the third dimension Disease, a distinction is made between Acute Disease and Chronic Disease. Goodwin et al. (2020) and Kondylakis et al. (2015) applied DTs for diabetic patients, while Semakova and Zvartau (2018) used a DT to classify chronic hypertension patients. Prado et al. (2002), on the other hand, dealt with acute end-stage renal disease. The dimension User can be used to differentiate between users from the Medical Environment and Non-Medical Environment. For instance, DTs were available to healthcare professionals and patients (Rivera et al., 2019; Maniadi et al., 2013), but also to athletes (Barricelli et al., 2020). Next, the dimension Individuality can classify whether the DT can be Personalized or Non-Personalized. According to Bruynseels et al. (2018), personalized medicine can be achieved through individual patient representation. For example, Björnsson et al. (2019) conceptualized an individual patient for selecting the most effective medication, while Naplekov et al. (2018) developed a coronary vascular system in general. In contrast, the representation of a group of people is categorized as non-personalized because there is no individual consideration. The sixth dimension Subdivision consists of three characteristics and categorizes whether the DT represents an Individual, a Group or Cohort, or a System. For example, Mazumder et al. (2019) and Niederer et al. (2020) used DTs to form healthy and unhealthy patient cohorts to compare the resulting data. Whether the DT is designed and updated with Medical Data or Non-Medical Data can be defined by the dimension Data. For instance, Croatti et al. (2020) utilized medical data derived from the hospital information system for a trauma DT, whereas El Saddik (2018) included data from patients’ social networks. The question of which sensors or devices are employed to collect these data is addressed in the following dimension Data Acquisiton. According to Martinez-Velazquez et al. (2019), data on

Table 1. Initial taxonomy of healthcare digital twins.

<table>
<thead>
<tr>
<th>Dimensions</th>
<th>Characteristics</th>
</tr>
</thead>
<tbody>
<tr>
<td>Representation</td>
<td>Cardiovascular or Respiratory</td>
</tr>
<tr>
<td>Medical Procedure</td>
<td>Prevention</td>
</tr>
<tr>
<td>Disease</td>
<td>Acute</td>
</tr>
<tr>
<td>User</td>
<td>Medical Environments</td>
</tr>
<tr>
<td>Individuality</td>
<td>Personalizable</td>
</tr>
<tr>
<td>Subdivision</td>
<td>Individual</td>
</tr>
<tr>
<td>Data</td>
<td>Medical</td>
</tr>
<tr>
<td>Data Acquisition</td>
<td>Smartphone</td>
</tr>
<tr>
<td>Data Security</td>
<td>Protected</td>
</tr>
<tr>
<td>Activity Level</td>
<td>Active</td>
</tr>
<tr>
<td>DT Modeling</td>
<td>Mechanical</td>
</tr>
<tr>
<td>DT Technology</td>
<td>Software</td>
</tr>
</tbody>
</table>
GPS, acceleration, or heart frequency can be collected through the Smartphone’s built-in sensors. Lutze (2019) used a Wearable by applying a smartwatch, while Buldakova and Suyatinov (2019) used biosignal Sensors. We were further able to identify that these data destined for DTs are either Protected or Non-Protected. The dimension Data-Security categorizes these two cases. Ersotelos et al. (2013) and Fagherazzi (2020) proposed to follow the privacy-by-design approach by leveraging the most advanced technologies like a cloud architecture to proactively protect privacy from invasive events. The tenth dimension Activity Level is based strongly on Chakshu et al. (2019) and categorizes an Active, Semi-Active, or Passive DT. An active DT continuously updates the data of the real Twin, a passive DT does not. In a semi-active DT, the data is time-variable. A mixture of active and passive DT models is also possible (Chakshu et al., 2019). Corral-Acero et al. (2020) defined that a DT arises from a synergistic combination of computer-aided induction and deduction. To construct a DT, both mechanical and statistical models are required, accordingly the dimension DT-Modeling distinguishes between Mechanical and Statistical or Mathematical models. The development of a realistic virtual model of the coronary vascular system was based on numerical modeling in the article by Naplekov et al. (2018). Corral-Acero et al. (2020) and Lauzeral et al. (2019), for instance, further developed their DTs based on the results of mechanical models. The dimension DT-Technology classifies whether Hardware or Software has been utilized for the conception and operation of DTs. For instance, Kifayat et al. (2010) employed SunSPOT as a physical sensor node for live-motion capture data, while Alcaraz et al. (2019) relied on Matlab for a memory polynomial model. By using software, data storage could be integrated or a DT be visualized. Zhao and Zhang (2013) implemented a data storage, while Zhao et al. (2013) displayed the DT on a website, and Ersotelos et al. (2013) provided a platform with various features to display or compare the results. Besides the visualization, Rahman et al. (2019) further implemented a serious game environment for gamification elements.

Subsequently, we demonstrate the applicability of this initial taxonomy. For this, the DT developed by Corral-Acero et al. (2020) was categorized according to our 12 dimensions and 35 characteristics, as depicted in Table 2. Grey highlights indicate that the particular characteristic(s) of the dimensions account for this DT. Thereby, each dimension allows more than one characteristic to be utilized for classification.

<table>
<thead>
<tr>
<th>Dimensions</th>
<th>Characteristics</th>
</tr>
</thead>
<tbody>
<tr>
<td>Representation</td>
<td>Cardiovascular or Respiratory</td>
</tr>
<tr>
<td>Medical Procedure</td>
<td>Prevention</td>
</tr>
<tr>
<td>Disease User Individuality Subdivision Data Data-Acquisition Data-Security Activity Level DT-Modeling DT-Technology</td>
<td></td>
</tr>
<tr>
<td>Medical Environments Personalizable Individual</td>
<td>Group or Cohort</td>
</tr>
</tbody>
</table>

Table 2. Taxonomy application on the cardiovascular DT by Corral-Acero et al. (2020).

A cardiovascular DT is conceptualized, and its role as an enabler of precision medicine is discussed in the paper by Corral-Acero et al. (2020). Thereby, the main emphasis is on the synergy between computer-enhanced induction and deduction (Mechanical, Statistical or Mathematical) for a valid and accurate virtual representation of a heart (Cardiovascular). The DT is intended to support medical professionals (Medical Environments) in the diagnosis, treatment, and prevention (Prevention, Diagnosis, Treatment) of heart disease (Acute, Chronic). Therefore, the patient-specific cardiovascular...
DT (Personalizable) is to be compared with population-based DTs (Individual, Group or Cohort) to enable a better clinical decision. For this purpose, the statistical and mechanical models are supplied with clinical data (Medical). The DT is intended to monitor each person’s lifecycle and integrate data collected by wearable sensors (Wearables, Sensors) as well as lifestyle information (Non-Medical). This information is to be dynamically collected and processed (Active) but is not yet protected (Non-Protected). The DT concept was a combination of software and hardware components (Software, Hardware) (Corral-Acero et al., 2020).

5 Discussion

As shown above, applying the taxonomy on a health-specific DT already offers promising results. The taxonomy provides a valuable basis for the categorization of this uprising technology in healthcare. Thereby, the mapping of real-world objects is purposely not limited to one characteristic per dimension, as otherwise relevant information would be excluded. This is in line with various taxonomy contributions (Buck et al., 2020; Püschel et al., 2016; Jöhnk et al., 2017) and even existing DT classification schemes (Kritzinger et al., 2018; van der Valk et al., 2020). Consequently, the criterion of mutual exclusivity, according to Nickerson et al. (2013) is neglected, and non-exclusivity is allowed for all dimensions of the taxonomy. The extensive character of our developed taxonomy allows a detailed assessment of existing DTs in healthcare. In comparison to that, existing DT taxonomies structured DT applications on a high level of abstraction. For instance, Kritzinger et al. (2018) categorized DT applications in the manufacturing industry with four classification criteria. Enders and Hoßbach (2019) formulated six dimensions. Likewise, the eight dimension-DT taxonomy developed by van der Valk et al. (2020) focused on general DT definitions. To gain insights into the relatively new applications of DT in healthcare and telemedicine, the result of the second iteration depicts the specifics of patient-centred digital health care. Due to the high number of dimensions, this in-progress taxonomy provides a basis for further iterations and application-specific concretization and practical utilization. For example, practitioners can deduce promising application fields and provide insights into DTs to enhance interest in the development and utilization thereof.

6 Conclusion, Limitations, and Future Research

This paper develops a taxonomy for categorizing DTs in digital health and telemedicine by applying the method of Nickerson et al. (2013). This taxonomy enables DTs to be implemented or transferred to telemedicine so that benefits can be derived and enhanced. The presented dimensions and characteristics provide a basis for answering the research question, as DTs can already be classified generally in the context of digital health. The application of a cardiovascular DT (Corral-Acero et al., 2020) already demonstrates the applicability of this classification approach. Besides, the conceptual-empirical approach of the first iteration already achieved several objectives. The conducted SLR (1) provided information on the current state of research, (2) created a basic understanding of DTs in healthcare, (3) provided a comprehensive insight into the implementation of DTs, and (4) identified existing concepts regarding initial dimensions and characteristics for the taxonomy.

The current state of the taxonomy is subject to several limitations. Regarding the methodological process, according to Nickerson et al. (2013), the taxonomy is not completed, as not all ending conditions are satisfied. Since this preliminary result relies on one iteration of the development process, the objective condition “no new dimensions or characteristics were added in the last iteration” (Nickerson et al., 2013, p. 9) could not be fulfilled yet. Likewise, the subjective conditions concise and robust are not yet satisfied. With 12 dimensions and 35 characteristics, a streamlining of these elements can enrich the taxonomy’s clarity. Miller's (1956) condition that the number of dimensions range between five to nine is consequently not satisfied. Besides, the subjective condition comprehensive cannot yet be determined. First, a larger sample of existing DTs from the healthcare sector must be classified according to this taxonomy. Nonetheless, the subjective conditions extensible and explanatory appear to be fulfilled. Dimensions or characteristics could be easily integrated, and potential correlations of health determinants could already be identified. Additionally, the two remaining objective ending
conditions are fulfilled after this iteration. Every dimension is unique and not repeated, while every characteristic of a dimension is unique as well. Beyond that, the result is generally limited. Firstly, the taxonomy's perceived usability depends strongly on the user's subjective preference (Nickerson et al., 2013). The current result lacks the assessment of medical experts who would implement and benefit from DTs in their daily work. At this preliminary level, the screening and exclusion process of SLR is likewise limited. The process was conducted by only one author and may be influenced by his subjective perceptions. Besides, the current taxonomy lacks the focus on telemedicine, resulting in the research question being only partially answered until now.

These limitations define the objectives and remaining aspects of future research. As every taxonomy is expandable, researchers can build on the existing taxonomy to expand or even reduce its dimensions and characteristics. The taxonomy can serve as a starting point for both researchers and practitioners that want to develop or implement DTs in digital healthcare and telemedicine. Additionally, an evaluated taxonomy will provide researchers with a solid foundation for further research, theory development, or theory testing. We aim to relate the presented results to telemedicine in order to enable targeted recommendations of DTs in telemedical care. These recommendations are intended to initiate and facilitate DT’s adoption into telemedicine, thereby enabling medical benefits such as improved quality of care or enhanced access to medical information (Ekeland et al., 2010). We aim to contribute with an iterative follow-up, based on an empirical-conceptual approach with semi-structured interviews, according to Myers and Newman (2007). This intends to evaluate and iterate dimensions and characteristics according to research- and practice-oriented experts in healthcare and DTs. Further, we approach the fulfillment of all ending conditions, which require the consolidation or elimination of certain dimensions and the further mapping of real-world objectives.

References


