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HEALTHCARE IN THE ERA OF DIGITAL TWINS: TOWARDS A DOMAIN-SPECIFIC TAXONOMY

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Abstract

The pursuit of physical and mental integrity is a fundamental instinct that has accompanied humankind since the dawn of time. Based on the digitalization modern medicine nowadays no longer has only access to self-collected information, but to information from almost all areas of the patients' lives, which makes it possible to create a digital representation of them. This digital twin opens completely new and until now unthinkable possibilities, not only in the field of monitoring and prevention, moreover it is the key to personalized medicine. However, unlike other domains, the healthcare sector lacks a structured approach to exploit this paradigm. Against this background, based on a systematic literature review and the methodological approach of Nickerson et al. (2013), the paper presents the essential dimension as well as characteristics of digital twins healthcare applications as a taxonomy that has been evaluated against 100 healthcare applications.

Keywords: Digital Health, Digital Twin, Healthcare, Taxonomy

1 Introduction

The concept of digitally representing physical objects to leverage the potential of *data-based optimization*, *decision-making*, or *monitoring* is central to *digital twins* (Björnsson et al., 2019; van der Valk et al., 2020; Tao et al., 2018). Initially, the concept experienced a lot of attention in typical engineering domains, such as *manufacturing*, *aerospace*, or *construction* (Saracco, 2019; Ricci et al., 2021; Bruynseels et al., 2018). It is not far-fetched to transfer traditional engineering concepts, such as 'predictive maintenance' or 'performance optimization' from artificial objects (e.g., machinery or airplanes) to human organisms (Bruynseels et al., 2018). Subsequently, the healthcare domain "(…) is one of the most promising fields for the use of digital twins" (Saracco, 2019, p. 59). For example, prediction of machinery failure by closely monitoring the physical asset and simulating its behavior seems transferable to concepts like 'predictive care' (Bruynseels et al., 2018). The design and implementation of appropriate application scenarios, taking into account the organizational context, not only has a significant impact on healthcare and the general well-being of patients, but also enables countless beneficial applications, e.g., personalized medicine, simulation of drug-effectiveness and tolerance, or data-based recommendations and alert systems. (Björnsson et al., 2019; Bagaria et al., 2019; Corral-Acero et al., 2020).

Significantly, having a valid digital twin of the human body would enable physicians to develop and simulate (i.e., predict the outcomes) therapies and monitor the behavior of organs (Barricelli et al., 2020; Zhang et al., 2020). Broadly speaking, the value of digital twins in healthcare resides in digitally representing healthcare-relevant physical objects (e.g., *patients*, *organs*) and leverage the potential of analyzing the resulting data or simulating effects of medicine or measure pre-physically (Barricelli et al., 2020; Chakshu et al., 2021; Corral-Acero et al., 2020). Subsequently, the notion of using digital twins in healthcare applications has significantly gained relevance in IS research. On a broader scale, exploring digital twins to assist *good health* is a promising research avenue and pays into the corresponding sustainability goal **(Goal 3)** of the *United Nations* (United Nations, 2015).

As of now, there is a lack of structure on how to use digital twins in the healthcare domain. From that results the need to "(…) organize the body of knowledge that constitutes a field (…)" (Glass and Vessey, 1995, p. 65) through structuring the existing knowledge in a *taxonomy*. Next to structuring the field of knowledge, taxonomies, as part of *descriptive-analytic theory*, help to understand the compositional structure of an object of interest and can be the basis to formulate prescriptive knowledge (Möller et al., 2021a; Gregor, 2006; Glass and Vessey, 1995). An existing body of research develops taxonomies and visualizes them in morphologies (e.g., see van der Valk et al. (2020)), which is a powerful and intuitive visual tool to deconstruct morphological characteristics of digital twins in healthcare applications (Szopinski et al., 2020; Ritchey, 2014). To summarize, we seek to structure the body of knowledge **(1)** and codify what we learn in initial guidance on designing digital twins in healthcare applications **(2)**. For that purpose, we propose the resulting taxonomy as a storage mechanism of knowledge on digital twins in healthcare, which can be extended in future research (Jacob, 2004). Because of the above, we see high value for a taxonomy of digital twins in healthcare and formulate our research question as follows:

What are the design dimensions and characteristics of digital twins in healthcare applications?

To answer the research question, we follow the method of Nickerson et al. (2013) and design a taxonomy of digital twins in healthcare applications. To generate data, we opt for a *systematic literature review* following Webster and Watson (2002). The short paper reports on the taxonomy after three design iterations and an evaluation cycle with empirical examples. The *short paper* is structured as follows. Following the introduction, we illustrate the background on *digital twins in healthcare*. Section 3 introduces our research design, which is followed by the taxonomy. In Section 4, we detail the taxonomy and illustratively apply it at the hand of empirical examples.

2 Digital Twins in Healthcare

The digital twin concept originates in NASA's Apollo Project, in which a physically identical *replica* of a space vehicle was kept on earth to mirror the conditions in space (Rosen et al., 2015). While the example did not use a digital twin, *per se*, but a physical one, it illustrates the concept of having an additional instance of an object to analyze and draw conclusions about the other. Digital twins do not have a standard unified definition but are characterized through a spectrum spawning various terminology (e.g., *digital shadow* or *digital angel*) (Wagner et al., 2017). Generally, a *digital twin* requires a physical object and a corresponding digital representation. However, it is not essential which comes into existence first (van der Valk et al., 2020). Transfer opportunities of digital twins in healthcare are mainly found in digital modeling of complete human bodies (for example, as a virtual patient) or individual organs to improve the quality of care for patients (Boer, 2020; Corral-Acero et al., 2020). These applications consider fitness applications, e.g., tracking athletic performance, which we assign to the healthcare domain (Barricelli et al., 2020).

For example, Chakshu et al. (2021) illustrate a scenario for using digital twins representing *cardiovascular systems* to enable patient-individual analysis through continuously monitoring data via a wearable device. Principally, that idea of 'copying' the physical person and representing it digitally is paradigmatic for digital twins in healthcare. Yet, the layer of abstraction the digital twin is supposed to address can vary drastically, both going beyond the scope of a 'single person' and below. While the former example particularly refers to people or patients, other research emphasizes representing only part of the human body, such as individual organs (Barricelli et al., 2020). Corral-Acero et al. (2020) report on digital twins of hearts by constructing statistical and mechanistic models. The drastically improving stream of data would be a significant enabler of precision medicine.

Similarly, Zhang et al. (2020) use the digital twin concept for ML-based prediction of lung cancer susceptibility in patients. Contrary to going more in-depth into the human body, other research reports on digital twins in hospitals in general. For instance, Karakra et al. leave the borders of viewing individual patients but propose digitally twinning a hospital to monitor pathways of patients in a hospital comprehensively. Contrary to biophysical data, the input would be architectural plans and sensors to identify a patient's position and map out clinical pathways accordingly. Additionally to only considering an individual object of interest (e.g., patient or hospital), Elayan et al. (2021) outline comparing digital twins of patients with digital twins with patients of comparable cases. That enables cross-learning between cases from patient histories and gives more data to avoid potential efficiencies in patient care further.

A sub-field of personal healthcare application is the fitness domain. That field, in particular, is very likely to have a high familiarity with the consumer market through various fitness-tracking applications used in modern wearable devices (e.g., smartwatches) and mobile applications, such as *Runtastic*. Generally, the purpose of the digital twin is to represent, for example, digitally, a professional athlete's performance-relevant fitness parameters (e.g., nutritional intake, sleep, or fitness activity) (Barricelli et al., 2020). A practical application uses real-time data from wearable devices in digital twins of athletes to give instant feedback once specific lifestyle performance parameters (e.g., nutritional intake) are not met. In that regard, the digital twin is an enabling technology to drastically increase efficiency in data-based coaching (Gámez Díaz et al., 2020). Significantly, a digital twin has the potential to map nutritional needs digitally, paving the way to highly individualized nutritional strategies in conjunction with self-monitoring applications, such as measuring and potentially manipulating the *Body-Mass-Index (BMI)* (Gkouskou et al., 2020).

3 Research Design

The *short paper* reports on the design of a taxonomy for digital twin applications in *healthcare*. We use Nickerson et al. (2013)'s method as it is the *de facto* standard for taxonomy design in IS research (Szopinski et al., 2019). The taxonomy design method prescribes seven steps, starting with the formulation of a *meta-characteristic* that reflects the taxonomy's overarching goal. In our case, it reads as follows: *'Design parameters for Digital Twins in Healthcare Applications'*. Next, one must specify ending conditions that terminate the taxonomy design process. We adopt the subjective and three objective ending conditions *("…least one object is classified under every characteristics","...dimension is unique and not repeated"* and "*…characteristic are unique within its dimension*") of Nickerson et al. (2013). In step 3, one must decide on choosing a *conceptual-to-empirical* or *empirical-to-conceptual* path to taxonomy design.

In the *short paper*, we develop the taxonomy through a *systematic literature review* following Webster and Watson (2002). Subsequently, we form the literature corpus of the last 10 years using standard databases, e.g., *Scopus*, *AISeL*, and *ScienceDirect* (see Table 1).

DataBase	Keywords	Hits	Titel & Abstract	Relevant
AISeL	("well-being" OR "health" OR "fitness" OR "wearables" OR "self-tracking") AND "digital twin"	41	0	0
ScienceDirect		163	5	1
Scopus		250	20	11
IEEE		58	14	6
ACM		65	4	1
WebofKnowledge		68	15	0
PubMed		19	8	7
Sum		**644**	**65**	**26**

Table 1. Literature Search Strategy.

We use a *concept-matrix* approach among the three authors to analyze the literature iteratively. We divided the literature sample equally into three parts, which we analyzed iteratively. Each analysis cycle is a taxonomy design iteration. In a fourth iteration, we evaluate our literature-based findings against a sample of 100 products in the healthcare and fitness domain. Two authors analyzed 50 samples independently. Subsequently, the taxonomy design process contained three literature-based design iterations and one based on empirical examples. Contrary to designing an utterly novel taxonomy, we draw from the "(…) *practical ethos* (…)" of design science research reusability and use an existing, domain-independent digital twin taxonomy as a starting point that we adapt to healthcare applications (Iivari et al., 2018, p. 1).

We chose to use the taxonomy of van der Valk et al. (2020) that proposes eight generic dimensions of digital twins. Specifically, we used the dimensions as *template codes* to categorize our healthcare-specific findings from the literature (Blair, 2015). Subsequently, the eight dimensions are a starting point and are a theoretical lens through which we analyze the literature (Niederman and March, 2019). Iteratively, we transform the domain-unspecific dimensions and characteristics for digital twins to those domain-specific for healthcare applications.

4 Preliminary Taxonomy of Digital Twins in Healthcare Applications

The taxonomy consists of ten dimensions with corresponding characteristics. We used the underlying literature sample and empirical examples to develop the taxonomy. The starting point was the generic taxonomy of digital twins of van der Valk et al. (2020), which we used as an initial theoretical lens to analyze the literature for domain-specific design dimensions and characteristics of digital twins. The characteristics of the dimensions can be mutually exclusive (M) or non-exclusive (N) (Möller et al., 2021b).

Dimension (Dn)		Characteristic (Cnm)						
Health Purpose	N	Self-Tracking	Diagnoses	Care	Prevention	Personali-zation	Assistants	Simulation
Health Functionality	N	Monitoring	Alerting	Recommendation				
User	N	Patient/User	Caregiver	Medical Professional				
Interface	M	Visual	Haptic					
Creation	M	Physical First	Digital First	Simultaneously				
Health Scope	M	Virtual Human	Localized Model	Infrastructure				
Data Synchronization	M	Ex Post	Real-Time	Mixed				
Data Source	N	Patient	Devices	Medical Records	External			
Data Types	N	Biomedical	Physical Activity	Behavioral	Dietary	Environmental		
Data Use	N	Personal Use	Share					

Table 2. Preliminary Taxonomy of Digital Twins in Healthcare Applications.

Initially, we conceptualize the application of the digital twin in a dimension **Health Purpose (D_1)**. Our analysis shows seven characteristics that determine what the digital twin in healthcare is supposed to do. We differentiate between *self-tracking* (e.g., using *smart scales*) **(C_{11})**, *diagnosing of diseases* **(C_{12})**, *care* **(C_{13})**, *prevention* **(C_{14})**, *personalized medicine* (e.g., therapies or medicine) **(C_{15})**, *personal assistants*, and *simulation* (i.e., testing how treatment works digitally) **(C_{16})**.

The second dimension details the **Health Purpose (D_1)** and focuses on **Health Functionalities (D_2)**. Functionalities follow a triad of integration of capabilities. The most fundamental characteristic is *monitoring* **(C_{21})**, which sees the digital twin as a tool used to view data. Typical application scenarios monitor weight on a scale or monitor patient data from afar by a medical professional **(C_{21})**. The functionality can be extended through *alerting* **(C_{22})** the user, for example, about irregularities in the data (e.g., *ventricular fibrillation*). Thirdly, the digital twin might be used to *recommend* **(C_{23})** a course of action or change in behavior (e.g., how to improve *sleep*).

We distinguish three types of **users (D_3)** (Strobel and Perl, 2020; Strobel, 2021a). First, the corresponding application is used by a person on himself, e.g., by using a smart device that measures biomedical parameters such as blood pressure or physical activity **(C_{31})**. Second, the application is used, by another non-medically trained person such as family members or friends **(C_{32})**. This includes data sharing. Medical professionals **(C_{33})**, in contrast, subsumes any type of medically trained personnel (nurses, internist, surgeon, etc.).

Interface (D_4) specifies the mode of interaction between digital information and the human being. Either the interface represents the data *visually* **(C_{41})** or *haptically* **(C_{42})**. For example, Bagaria et al. (2019) report using wearable devices in *sports* that give haptic feedback to its wearer. In that particular case, the feedback is an indication of when to sprint.

We adopt the dimension **Creation (D_5)** directly from van der Valk et al. (2020)'s taxonomy, as we could not identify healthcare-specific characteristics that would have led us to deviate from it. A digital twin must exist both in the physical world and the digital, leading to the underlying question of which should exist first (van der Valk et al., 2020). Our empirical examples reveal that, usually, the digital twin starts with the physical counterpart **(C_{51})**. For instance, we found examples of constructing digital twins of dentures using sensory-equipped smart toothbrushes or monitoring heart rates through sensory-equipped vests. Ricci et al. (2021) report on digital twin applications in pre-hospital care processes constructing digital twins, for instance, vehicles, and feeding them with real data afterward, making the digital part come first **(C_{52})**. Lastly, the time of creation can be *simultaneously* **(C_{53})**.

As each digital twin requires a physical counterpart, one must settle on a level of detail and abstraction and demarcate the object of interest that is supposed to be digitized, i.e., define the **Health Scope (D_6)**. We see a three-part division. Firstly, a *comprehensive model* of a patient or an entity of analysis (Chakshu et al., 2021) **(C_{61})**, a *localized model* **(C_{62})** (e.g., of the heart) (Corral-Acero et al., 2020), or *infrastructure* (e.g., of clinical pathways (Karakra et al.)) **(C_{63})**.

Data Synchronization (D_7) describes whether the data is transferred and analyzed *ex-post* **(C_{71})**, i.e., after data collection or in *real-time* **(C_{72})**. Lastly, the third characteristic *Mixed* **(C_{73})** unifies both characteristics.

The availability of suitable **Data Sources (D_8)** is an essential prerequisite for using the digital twins. First and foremost, the *patient* **(C_{81})** as the archetype of the digital twin is the center of attention. In addition to the qualitative and quantitative data provided by the patient, the automatic collection of data in everyday life or during diagnostic processes plays a crucial role to fulfill the medical objective. Dedicated sensors (e.g., temperature, oz-load), smart products (e.g., fitness trackers, blood pressure monitors, smartwatches) but also clinical medical devices (e.g., MRI, MRT) are used to record the necessary data (*device* **(C_{82})**). *Medical records* **(C_{83})**, on the other hand, aggregate these collected data and combine them with medical expertise. Thus, contain a significant variance of different data such as medical history, laboratory values, X-rays, or even complete doctor's letters (Strobel and Perl, 2020). In addition to medical information, they also contain organizational or legally relevant information (e.g., insurance status, medical bills, and living wills). The dataset is often enhanced with *external data* to enrich the database or increase the digital twin's information quality **(C_{84})** (e.g., weather, ozone values, pollen load) (Strobel and Perl, 2020).

The **Data Types (D_9)** are similarly diverse as the data sources. The focus is on smart data automatically generated through sensors and smart products and enriched with further information from the user (Strobel, 2021b). Based on empirical observation and following the prevailing definition in the literature (Strobel and Perl, 2020), five key data types can be identified:

- **Biomedical:** e.g., blood pressure, glucose or heart rate **(C_{91})**
- **Physical activity:** e.g., stepcount, activity status or sleep cycles **(C_{92})**
- **Behavioral:** real-time location **(C_{93})**
- **Dietary:** e.g., caloric intake or nutritional information **(C_{94})**
- **Environmental:** e.g., humidity, temperature,noise pollution or particulate matter **(C_{95})**

The dimension **Data Use (D_{10})** includes two characteristics. First, the use of data is restricted or targeted to the user or patient (e.g., usually in a smart-scale) **(C_{101})**. Second, the data can be shared with third parties, e.g., family members involved in the care of elderly persons or a medical professional remotely monitoring conditions of patients **C($_{102}$)**.

5 Illustrative Application

Demonstrating the usefulness and applicability of the taxonomy is an essential step in the taxonomy development process (Nickerson et al., 2013). Against this background, we used an *empirical-to-conceptual* iteration to evaluate the literature-based findings or extend the taxonomy accordingly. Subsequently, we constructed a database of 100 empirical examples ranging from *fitness trackers* and wearable ECG measuring devices to applications for indigestion analysis (including, e.g., smart scales, remote monitoring devices, or sleep trackers). Furthermore, when selecting the sample, we ensured that it included both end-user devices (e.g., *FitBit Charger 3*) and B2B solutions (e.g., *Wearable Bio Patch*). To illustrate the applicability of the taxonomy, we present two of the 100 digital twin applications from our sample in further detail.

Dimensions	Comarch CardioVest	Choose Muse
Health Purpose	Prevent, Diagnose and Supervise Cardiac Disorders **(Prevention, Diagnosis, Care)**	EEG-Powered sleep tracking **(Self-Tracking)**
Health Functionality	Analyzes data through a *telemedicine platform* and identifies deviations **(Monitoring, Alerting)**	EEG-Powered sleep tracking **(Monitoring)**
User	**Patient** and **Medical Professional**	User of the headband **(Patient)**
Interface	Analyzes data through a *telemedicine platform* **(Visual)**	Feedback on Mobile Application **(Visual)**
Creation	**(Physical First)**	**(Physical First)**
Health Scope	Focus on partial aspect - ECG **(Localized Model)**	Focus on partial aspect – EEG/Brain **(Localized Model)**
Data Synchronization	Analysis after 24 hours of measuring **(Ex-Post)**	Real-Time Feedback **(Real-Time)**
Data Source	ECG Vest **(Device)**	Brain-sensing headband **(Device)**
Data Types	ECG Data **(Biomedical Data)**	Brain Activity, Movement **(Biomedical Data, Physical Activity)**
Data Use	Monitoring Center for Care **(Share)**	Data is not shared **(Personal Use)**

Table 3. Illustrative Examples.

Comarch CardioVest[1] is a wearable ECG measurement device with the objective of prevention, diagnosis, and care of cardio-vascular events. The focus of the application is the reduction of lengthy ECG examinations in clinics or specialist practices. The vest is applied by the patient independently without interaction with medical professionals. The recorded ECG signals are transmitted in fixed time

1 https://www.comarch.com/healthcare/products/remote-medical-care/remote-cardiac-care/comarch-cardiovest - last accessed: 28-04-2021

corridors to a cloud-based evaluation platform, which analyzes these data ML-based and interprets deviations in the curve progressions. Before the results are transmitted to the patient, they are verified again by medical professionals.

Choose Muse[2] is a wearable device for EEG-based meditation and sleep tracking. The headband is primarily based on the analysis of biomedical data (e.g., heartbeat, pulse, etc.), focusing on the analysis of brainwaves (e.g., alpha, beta, etc.) combined with movement parameters to support the user in meditation and targeted sleep. The objective of the application is the monitoring and visualization of the parameters, which is done via a wireless connected device (e.g., smartphone). The data is directly visible to the user without review or interpretation by qualified personnel.

In addition to the applicability of the taxonomy, further insights into the relationships and the interactions between the dimensions and characteristics could be obtained in the classification process. We demonstrated that self-tracking, which has become more and more of a trend in recent years, is also the central goal of most digital twin applications in the healthcare sector, accounting for around 50% of the sample. This is followed by diagnosis (18%) and prevention (14%), used in many cases as primary and secondary goals. Central data sources are devices (81%) such as smart inhalers, scales, or baby socks that record various biomedical data (61%), monitor them (63%), and alert (22%) the user in case of deviations via a visual interface (88%).

However, some applications also use haptic feedback, such as the Upright Go 2, which uses vibration to alert the user to incorrect or relieving posture and correct it. Furthermore, as expected, patients (65%) are the central user group, but they increasingly share their information directly with other user groups, such as the treating practitioner (18%). Detached from the broad variance of devices, the spectrum of capabilities of smart products (Porter and Heppelmann, 2014) shows that the DT solutions currently offered are more likely to be used for activities at the lower end of the spectrum, such as monitoring. Particularly due to the existing database, the potential in the field of simulation and personalized medicine is not fully exploited.

6 Contributions, Limitations, and Next Steps

Our paper proposes a taxonomy of digital twins in healthcare applications. First, we contribute to **research** by organizing the body of knowledge on designing digital twins in healthcare. We clarify and illustrate designable dimensions of digital wins in Healthcare, contributing to their understanding and assisting practitioners and researchers in creating them. Given that our research produces a visualized taxonomy as a morphology, it enables innovating existing digital twin applications or finding new healthcare ones. Subsequently, our work can contribute to leveraging the spectrum of application scenarios in healthcare and fitness.

Naturally, our work is subject to **limitations**. Given the nature of the *short paper*, we report on the current state of research up to the point of submission. While we report on a preliminary taxonomy that is already based on a systematic literature review and 100 empirical examples, it yet requires more work to grasp the field and find theoretical saturation fully. Additionally, even though we drew from an existing generic taxonomy, the resulting dimensions and characteristic, naturally, are prone to being subjective. Other researchers might identify different dimensions or find others to be more critical.

In the **next step**, we will advance the further empirical grounding of the taxonomy and iterate it to the point of *theoretical saturation*. The foundation for this will be an expansion and healthcare-oriented specification of the literature sample based on the Top Basket of the AIS SIG Health. To identify that point precisely, we follow the ending conditions of Nickerson et al. (2013). Once the iterative design has finished, we see two necessary avenues. First, the evaluation in a setting with either researchers or practitioners familiar with digital twins in healthcare either through domain or methodological expertise (Szopinski et al., 2019). Second, a common avenue to leverage the full potential of empirically generated taxonomies is to develop archetypes of the object of interest. In our case, we aim to develop *archetypes*

2 https://choosemuse.com - last accessed: 28-04.2021

of digital twins in healthcare applications based on a *cluster analysis* of an extended empirical database. That avenue of further research is especially valuable, as we can develop foundational patterns of digital twin configurations in healthcare that can be copied or used as a basis to extend or draw inspiration from. Furthermore, it would be conceivable to specialize the taxonomy for individual sub-areas of healthcare and to enrich it with specific dimensions and characteristics. Third, in a later stage, one could develop design principles as codified prescriptive design knowledge based on the design dimensions of the taxonomy. Subsequently, our research would then be extended with prescriptive design knowledge that can be developed in *a priori* and empirically developed design dimensions (Möller et al., 2021a).

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