Categorization of Digital Twins: A Literature Review of IoT and Industry

1st Jere Grönman
Tampere University
Pori, Finland
jere.gronman@tuni.fi

2nd Petri Rantanen
Tampere University
Pori, Finland
petri.rantanen@tuni.fi

3rd Mika Saari
Tampere University
Pori, Finland
mika.saari@tuni.fi

***Abstract*—In recent years, the digital twin concept has gained traction in both academia and industry. But what is a digital twin? It is quite common to see many kinds of publications from scientific research to news articles on digital twins mentioning that there is no exact definition for the term. In this paper, we will go through the digital database of IEEE Xplore in an attempt to find out how the publications on digital twins use the term, and how the twins could be categorized and defined more clearly. Our focus is on literature that studies the digital twins within the context of Internet-of-Things (IoT) and industry. Our studies will show that there is indeed a need for a more standardized definition for the term, and that *digital twin* is often used as a blanket term to cover many systems, prototypes and implementations that may or may not be actual digital twins.**

***Index Terms*—Digital Twin, Literature Study, Maturity, Categorization, Industry**

I. Introduction

There is a quite often seen myth about the digital twin originating in the NASA Apollo program[1], but generally, the origin of the digital twin concept is generally accredited to Michael Grieves and John Vickers [1]. In its most generic terms, a digital twin is a digital representation of a real-world physical system or process. Nevertheless, it is not uncommon to see publications mention that the term perhaps does not have a clearly defined meaning, or that the meaning varies between (research) fields, and industries.

The motivation for the work presented in this paper comes from the ongoing *Practical applications of Digital Twins in the Satakunta region* project, which studies how small and medium-sized companies in the Satakunta region of Finland could take advantage of digital twins in their daily business. As a background research for the project we looked at the literature of digital twins, and it quickly became apparent that there might indeed be a huge variance in how the term *digital twin* is used, and especially the discussion on the nature of the digital twin (e.g. maturity, complexity) can be quite vaguely expressed. Thus, we wanted to take a more in-depth look at the digital twin research on industry in particular, and find the answers to the following research questions:

RQ1: Is it possible to discover the maturity and complexity of digital twins presented in scientific literature?

and

RQ2: How to categorize research related to digital twins in the scope of IoT and industry?

The rest of the paper is structured as follows: Section II gives background information on the categorization of digital twins. Section III describes the process of our literature study, and Section IV discuss the study's results. Finally, Section V presents the conclusions of this study.

II. Background

According to [1], a digital twin is a virtual representation of a physical object, process, or system that can be used to simulate, monitor, and optimize its performance, and it is essentially a virtual copy of the physical asset, which can be analyzed and tested without the need for physical intervention. There is a wide range of potential application, such as manufacturing, construction, healthcare, transportation and energy, and they can be used to model a wide range of physical objects and systems, including buildings, factories, aircraft, and even entire cities. Digital twins are created by integrating data from multiple sources, such as sensors, software, and other systems [2]. Digital twins have the potential to revolutionize the way physical objects and systems are designed, built, and operated. They can help companies improve efficiency, reduce costs, and enhance safety, making them a valuable tool in a wide range of industries. The key benefits of digital twins, as listen by [3], are:

- Improved performance: Digital twins can help optimize the performance of physical objects and systems by simulating and analyzing their behavior in real-time. This can lead to increased efficiency, reduced downtime, and improved productivity.
- Predictive maintenance: By continuously monitoring the performance of physical assets, digital twins can identify when maintenance is needed, reducing the risk of unplanned downtime and improving asset lifespan.
- Cost savings: Digital twins can help identify areas for cost savings by optimizing the performance of physical objects and systems, reducing waste, and improving efficiency.

[1]History of the term is explained by Michael Grieves in his Linkedin post about "Physical Twins, Digital Twins, and the Apollo Myth," found online at https://www.linkedin.com/pulse/physical-twins-digital-apollo-myth-michael-grieves

- Enhanced safety: Digital twins can be used to simulate and test potentially dangerous scenarios without risk to human life or physical equipment, improving safety in high-risk industries.
- Better design: Digital twins can be used to test and optimize the design of physical objects and systems before they are built, reducing the need for costly rework and improving quality.
- Remote access and monitoring: Digital twins can be accessed remotely, allowing teams to monitor and manage physical assets from anywhere in the world.
- Improved collaboration: Digital twins can help improve collaboration between different teams and stakeholders, enabling better decision-making and more effective problem-solving.

In the development of digital twin technology maturity levels are important because they provide a framework for measuring progress and identifying areas for improvement. By assessing the maturity level of a digital twin, organizations can determine how advanced their technology is and what steps they need to take to improve it. Maturity levels can also help organizations benchmark their digital twin development against industry standards, best practices, and competitors. This can provide valuable insights into how well their digital twin technology is performing and where they need to focus their efforts to stay competitive. [4]

In [3], a maturity model consisting of three levels for the AECO (architecture, engineering, construction and operation) sector was proposed. The first level is the monitoring platform, which enable the sensing of physical assets and reporting. The second level is the intelligent semantic platform, which leverage semantic approaches to provide some degree of asset intelligence, with feedback and control carried out by experts. The third level is the agent-driven socio-technical platform, which have a larger degree of intelligence and autonomy driven by machine learning approaches.

A six-level maturity spectrum was presented in [4], with level 0 involving reality capture such as drawings and sketches. Level 1 consisted of a 2D/3D model without any metadata, while level 2 incorporated some static data with the 3D model. At level 3, real-time data from sensors was included, and level 4 involved two-way data integration and interaction. Finally, level 5 represented autonomous operations and maintenance with complete self-governance, as well as total oversight and transparency.

According to [5], a maturity model with four levels was presented. The initial level was referred to as the pre-digital twin, in which only a model was available without any connection to the physical world. The second level was the digital twin, which interacted with the physical world, for example, by receiving maintenance data from sensors. The third level was the adaptive digital twin, which possessed machine learning capabilities and could obtain real-time updates from sensors. The fourth level was the intelligent digital twin, which had a higher degree of autonomy and employed reinforcement learning.

In [6], a maturity model consisting of three levels to measure increasing digital twin capabilities for manufacturing was proposed. The first level is supervisory, in which only passive monitoring is used by collecting data streams from the instrumented physical asset. The second level is interactive, in which the digital asset has some degree of control over the physical asset. The third level is predictive, in which the digital twin performs predictions leveraging the collected data and simulation techniques.

III. Literature survey

The research method is based on a systematic mapping study. According to [7], a systematic mapping study is designed to give an overview of the research area by classifying and counting contributions in relation to the categories of the classification. The main difference between the systematic literature review method [8] and a systematic mapping study is the need to provide an update of how to select studies during the research when conducting a systematic mapping study. For the selection of the studies, we decided to perform an online search. We used the search engine and database of articles in IEEE Xplore Digital Library. The keywords used are listed in Table I. The plus sign (+) in the table means that the terms were given as a combination of terms for the IEEE Xplore's search query. The words without the plus sign mean a single search term (e.g. *digital twin*). The keyword selection process is described below:

1) The keyword selection process was started by testing keywords related to the goals of our project. We wanted to exclude publication that were not related to industry or digital twins. The terms *industry* and *industrial* return slightly different results when given to the IEEE Xplore's publication search. Unlike the terms *digital twin* and *digital twins*, which return identical results - and in this case, we chose to only use the former term.
2) Unfortunately, as can be seen in Table I, these terms return both individually and in combination too many results to be practically possible to fully analyze all of them. The Internet-of-Things (IoT) is a term quite often associated with both modern industry and with digital twins. Thus, the term *iot* was added as a search term, bringing the number of publications to a more manageable amount, but also to bring a slightly more limited focus to this study.
3) The final search terms *digital twin* + *iot* + *industry* and *digital twin* + *iot* + *industrial* were checked for duplicate results, and after removing the duplicates, the total amount of publications was **183**.
4) From the remaining 183 publications, a total of 23 survey or review papers, and a total 41 otherwise invalid results were further removed, bring the final number of publications to **119**. These removed publications are further discussed in Subsection III-A.

By looking at Table I, several additional observations can be made. Our initial idea was to limit the publications to the past five years (2018-2023), but as can be seen in the table, the term *digital twin + iot + industry* has no result before the year 2018, and the term *digital twin + iot + industrial* has only two publications before the year 2018, with both being published in or after 2016. Consequently, we decided to include all publications of the two search terms in this study. As a general note, as can be seen in the table, a high percentage of all publications related to the listed search terms were published in the past five years.

TABLE I
THE PUBLICATION AMOUNTS FOR EACH KEYWORD AND KEYWORD COMBINATION. THE FINAL SELECTED KEYWORDS ARE MARKED IN GREEN COLOR.

	Number of publications		
Keyword(s)	**All publications**	**First publication**	**2018-2023**
digital twin	3656	1964	3266
iot	68046	1991	54477
industry	303172	1885	96089
industrial	321315	1885	103766
digital twin + industry	969	1986	951
digital twin + industrial	935	1991	897
digital twin + iot	352	2016	347
iot + industry	8030	2000	6828
iot + industrial	7313	2000	6188
digital twin + iot + industry	142	2018	142
digital twin + iot + industrial	135	2016	133

Another observation of worth is that the first publication for the term *digital twin* is from the year 1964. This is because even when giving the keywords for the IEEE Xplore's search as a single term, the results can still include publication where these terms appear separately (i.e. not after each other), causing unwanted publication to be included in the results[2]. The terms *Internet-of-Things* and *Internet of Things* (which return identical results) have similar problems, with the terms *Internet* and *things* being too common for finding valid results. For this reason, we have only used the term *iot*, with the assumption that paper discussing the Internet-of-Things would also include the acronym IoT.

A. Excluded Publications

As mentioned before, a total of 41 publications were removed as invalid or unwanted results. The majority (26) of removals were because the paper was deemed not to discuss the wanted topics (digital twins, IoT and industry) in a required depth. In practice, this meant publications that only mentioned the terms in the abstract or introduction section, in the keyword list, or only in a single sentence, with the main research contribution being on some other (in this case) irrelevant topic. Twelve (12) publications were removed for being clearly incorrect results, with the terms not appearing in the publications at all, or only being present in, for example, the name of the authors' institution, organization or in author biography. The twelve removed publications also included three non-scientific results (two posters and one tutorial). And finally, three (3) publications were removed for their non-technical nature, the papers being questionnaire surveys. The final three removals discussed the wanted topics, but on such an abstract level, that in the scope of this study, we decided not to include them in our publication categorization.

Also, within the publications found with the selected keywords, a total of 23 literature reviews or surveys were discovered. Interestingly, these 23 surveys are over 16 percent of publications (16 % of 142 = 183 total - 41 removed) remaining after removing the unwanted results listed above, a number that feels surprisingly high. In any case, the publications related to the security aspects of digital twins were studied by [9]–[11]. The research on smart cities was explored by [12], [13]. The challenges and possibilities of smart manufacturing were studied by [14]–[16]. The trends in building information modeling (BIM) were analyzed by [17], and predictive maintenance by [18]. A review of digital twins in robotics was executed by [19], [20]. The publications on the sustainability of digital twins were studied by [21]. Surveys on healthcare, oil and gas industry, Metaverse and machine learning algorithms were performed by [22], [23], [24], and [25], respectively. And finally, [26]–[31] review the technologies and standards of digital twins. Thus, the surveys cover a wide range of existing publications. The paper [26] also lists several other literature surveys about digital twins. Still, only [28] considers analyzing the level and maturity of digital twins presented in publications, but the main content of the publication is in discussing the challenges and open questions of digital twin research. The observations of [28] relevant to our study are briefly analyzed in Section IV.

It should also be noted that the surveys listed above contain many publications not directly related to our research topics, and in the context of this study we did not browse through the listed surveys in an attempt to find more publication related to our topics, but only included the publications originally returned by the IEEE Xplore's digital library. Thus, this study does not contain *every* publication related to digital twins, IoT and industry, but only those included in the IEEE Xplore's database.

IV. RESULTS OF SURVEY

Multiple terms and categories are used in the literature to describe digital twins. For example, [32] and [33] provide a more in-depth look on the terminology used in the research publications. In this study, we use the three-level categorization used by [34]. I.e., we divided the digital twins presented in the publications into *models*, digital shadows and ("proper") *digital twin*. More specifically, we categorize studies that explore only the modeling aspects of digital twins (without a connection between the physical world and the digital or virtual world) as models, works that present solutions that only consider one-way information (or data) transfer (from physical to digital, e.g. using various sensors) as digital shadows, and research that includes both directions of information flow (from physical to digital, and vice versa) as digital twins. In

[2] A paper by M. S. Abou-seada and E. Nasser, "Digital Computer Calculation of the Potential and Its Gradient of a Twin Cylindrical Conductor," from IEEE Transactions on Power Apparatus and Systems, vol. PAS-88, from the year 1969, is a good example of unrelated paper, which is found by the given keywords because the terms *digital* and *twin* are present in the title.

many cases, the studies present the "proper" digital twin concept in introduction, related studies or future studies sections, but the presented work, prototype or implementation only considers one-way information (or data) transfer (e.g. because of practical limitations or research focus). These works are categorized as digital shadows. In the context of this study, this kind of categorization is called *type* categorization, and the results of this categorization can be seen in Table II.

TABLE II
CATEGORIZATION OF PUBLICATIONS BY TYPE.

		Publications	% of all publications
Type	Model	13	11
	Shadow	52	44
	Twin	40	33
	Unknown	14	12
	Total	119	100

While studying the publications, we found out that only two publications categorized their own work as research on digital models or digital shadows, all other works simply use the term digital twin, even when the model-shadow-twin paradigm was presented in the background section of the publication, and the paradigm was defined identically as we present it in this publication. And by looking at Table II, it can be seen that two-thirds of the works were in fact not digital twins based on that definition. Similar observations were made in [28], where approximately 54 percent of the analyzed 26 total papers claimed to be study digital twins, but actually studied either models or shadows. Table II also contains 14 (*unknown*) publications, which either did not contain any examples of their digital twin implementation, or the work was presented in such a way that it was not possible to categorize the work.

TABLE III
CATEGORIZATION OF PUBLICATIONS BY MATURITY.

		Publications	% of all publications
Maturity	Category 1	47	40
	Category 2	23	19
	Category 3	23	19
	Unknown	26	22
	Total	119	100

As was discussed in Section II, the literature contains several categorizations for the digital twin maturity. Initially, we attempted to match the research works on the existing maturity categories, but unfortunately, not a single publication included discussion about the maturity level of their work, or referred to the existing literature on categorization, making conclusive analysis of the research work very challenging. Thus, instead of using the pre-made categories, we used a more simplified 3-category system derived from the nature of the published works. In general, the works can be divided into three detectable maturity levels, which are presented here as Category 1, 2 and 3, and the number of publications related to each category can be seen in Table III. In the context of this study, this categorization is defined as presenting the maturity of the digital twin. The three categories are:

1) **Category 1** contains works, where the primary purpose is to represent (or visualize) information (for example, by the means of a user interface, figures, diagrams or 3D models). In the systems of this category, the user(s) must often react at least on some level on the presented information. This could be, for example, a 3D model of a sensor-enabled building.
2) **Category 2** contains works, where partial automation is present. For example, machine learning or AI is used to optimize or improve the process or function of a device. However, the system is not fully autonomous, and some reaction from the user is required, such as accepting the decisions made by an AI, or inputting initial or updated data to the system. This could be, for example, a digital twin of a hospital, where medical personnel must accept the recommendations made by the system, even when data collection and analysis are fully autonomous.
3) **Category 3** contains works that present fully autonomous systems, which do not in normal operation (excluding failures and error situations) require any interaction with users. A smart logistics center, where incoming packages would be sorted, processed and sent forward automatically, would be one example system.

If a publication describes a digital twin that includes multiple categories, they are ranked based on the highest category. I.e. Category 3 system may contain elements from Category 1 and Category 2, but must also be capable of functioning in the way required by Category 3. As can be seen in Table III, less than one-fourth of the works reach Category 3, and approximately 40 percent of the works simply illustrate or model the data, without more advanced features. The table also contains the *unknown* for works, that we could not categorize because of the limited examples or descriptions provided in the publication.

TABLE IV
RELATION OF MATURITY AND TYPE CATEGORIZATION.

		Type				
		Model	Shadow	Twin	Unknown	Total
Maturity	Category 1	7 (15 %)	37 (79 %)	3 (6 %)	0 (0 %)	47
	Category 2	2 (9 %)	7 (30 %)	13 (57 %)	1 (4 %)	23
	Category 3	1 (4 %)	3 (13 %)	19 (83 %)	0 (0 %)	23
	Unknown	3 (12 %)	5 (19 %)	5 (19 %)	13 (50 %)	26

Table IV presents the relation of the digital twin maturity to the twin's type - how many of each type of digital twins were on each maturity category, and the percentage of total publications of each category (in brackets). By looking at the table, we can see that the majority of works are of Category I digital shadows, i.e. research that presents systems that collect data, and visualize data to users. As could be expected, most of the Category 3 works also study a full digital twin. Furthermore, we can see that in cases where it was challenging to discover the type of the digital twin, it was more often (in half of the cases) also challenging to derive the maturity of the twin.

V. Conclusions

It is quite common to see research (and other publications as well) on digital twins mention that there is no clearly defined definition for the term *digital twin*, but perhaps it would be more accurate to say that there are multiple definitions for digital twins, and these definitions are not used in consistent fashion. Considering our first research question:

RQ1: Is it possible to discover the maturity and complexity of digital twins presented in scientific literature?

The answer seems to be, that using the more complex categorization schemes presented in literature, it is not possible, but using more simplified categorization, as presented in this paper, it is. In fact, the model-shadow-twin categorization used also by other authors before, and the maturity categorization presented in this paper can be considered an answer to our second research question:

RQ2: How to categorize research related to digital twins in the scope of IoT and industry?

Unfortunately, most of the studies, even when they present the model-shadow-twin paradigm, are very vague on how their own work relates to the paradigm. Similar observations can be made of the analysis of digital twin maturity. Understandably many of these studies are present prototypes or partial implementation, which cannot be expected to describe a full digital twin, but there are many publications that seem to use the term *digital twin* incorrectly either because of misconceptions related to the term or for promoting their work in the digital twin research field. There also seems to be some variance on the digital twin's definition based on the research field. Based on the study of the publications, it seems that it is more common in smart city or building information modeling context to define digital shadows as digital twins, when as in, for example, manufacturing industry, it is more common that digital twins are actually digital twins. Perhaps because implementing, for example, a full digital twin of an entire city is quite a challenge, in these cases the authors tend to use the term more freely.

In any case, it is important to note that the maturity categorization presented in this paper, or the model-shadow-twin paradigm in no way describe "betterness". Category 3 is not superior to Category 2, nor is digital twin superior to digital shadow, but each should be used when applicable. There are many cases, where, for example, fully autonomous operation is not desired (e.g. hospitals), or is practically impossible. Currently, the wild usage of the term *digital twin* makes it quite a challenge to find works that specifically study digital models or digital shadows, even when those works would be equally important as research on digital twins. Thus, based on our observations, the field is in dire need of standardization in both the definition and usage of digital twin terminology. This would help to categorize the works, systems and implementations, and lower the threshold of finding relevant research.

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