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Improving Digital Twin Experience Reports

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Abstract:
Digital twins (DTs) are prevalent throughout industrial domains as evidenced by the rapid pace of experience reports in the literature. However, there remains disagreement about the precise definition of a DT and the essential characteristics in the DT paradigm, such as the scope of the system-under-study and the time-scale of its communication with the DT. These experience reports could therefore be hampering further classification and research insights by not reporting all of these relevant details about the DT solutions. We address these concerns by providing a conceptual structure for DTs as a common understanding and checklist for researchers and practitioners to precisely describe the characteristics and capabilities of their DT solutions. We express five experience reports using our structure to demonstrate its applicability and role as a guideline to improve the reporting of characteristics and increase the clarity of future experience reports.

1 INTRODUCTION

The *digital twinning* concept has seen a recent explosion of interest in industry as system designers, manufacturers, and users explore the possibilities of having a digital version of their *system-under-study* (SUS) available for simulation. This is seen in multiple domains at multiple levels of detail, from digital versions of factory machines (Min et al., 2019) to energy management for a district in Helsinki (Ruohomäki et al., 2018).

Grieves *et al.* introduced the term 'digital twin' (DT) in 2002 in the context of *product lifecycle management* (Grieves and Vickers, 2017). A DT was either the digital version of the premanufactured product through the design cycle, or a digital version of the product in use that evolves to capture relevant detail and behaviour. This definition has expanded to be applied to further domains, such as "a DT is a virtual instance of a physical system (twin) that is continually updated with the latter's performance, maintenance, and health status data throughout the physical system's life-cycle" (Madni et al., 2019).

The promise of DTs is their ability to reason about the system's behaviour in the past, present, and future under different conditions, enabling advanced system error detection and prediction, visualization, optimization, or other activities (Rasheed et al., 2020). For example, maintenance could be automatically scheduled by the DT for machines based on the wear-and-tear data collected from sensors (Werner et al., 2019). These reasoning opportunities arise due to the combination of established modelling and simulation techniques with recent technological capabilities such as the Internet of Things (IoT), inexpensive computing power, and *big data* techniques (Tao et al., 2018a). This combination means that (in a mature DT) a large amount of SUS data is available for the DT to reason about, simulations can be run faster-than-real-time to optimize the system's trajectory, and the SUS can be automatically controlled for maximum performance.

Fuller *et al.* offer a comprehensive examination of the DT concept (Fuller et al., 2020) by providing an overview of definitions, a description of key challenges, and enabling technologies for DTs. A literature survey divides works into the manufacturing, healthcare, and smart city domains.

Both the work of Fuller *et al.* and our own rely upon the classification of (Kritzinger et al., 2018). It separates the concept of DTs into *digital models*, *digital shadows*, and *digital twins* based on the automation of the information connection present. In a *digital model*, the *information flow* (see Section 3.2) between the digital model and the SUS is not automatic and all incoming and outgoing information from the digital twin is manually communicated and manually acted upon. In a *digital shadow* (also termed a 'tracking simulator'), the incoming information such as a data stream is automated but there exists no automatic outgoing information being acted upon. Finally, *digital twins* have both an incoming and outgoing automatic information flow with the SUS, such as outgoing automated control commands.

Identified Issues. We identify three key issues in the DT literature: *a)* essential details about the *DT solutions* (digital model, digital shadow, or digital twin) are often not clear in experience reports, *b)* this leads to uncertainty about the capabilities of DT solutions and their classification, and *c)* the lack of multiple standard classifications then leads to miscommunication about how practitioners view DTs in their domain.

The communication between the DT and the SUS often lacks precision in experience reports. In particular, whether the *actions* requested by the DT are automatically or manually performed, at what *time-scale* (real-time, slower-than-real-time) these operations happen at, or the *acting* and *sensing component* modifications required to the SUS to support the DT. These details are essential for researchers to properly characterize the DT solution, understand their use by practitioners, and develop further insights into the classifications, usage, and possibilities of DTs.

For example, it is unclear if the experience report presented in Section 2 has been misclassified by (Fuller et al., 2020) as a *digital shadow*, rather than a *digital twin*. This is due to uncertainty whether there are automatic actions performed by the DT solution in that report.

From the literature, it also is clear that there is still uncertainty about what a DT is. The authors have heard practitioners specify that the DT must be used for real-time control of a system for it to be a "true" DT, as in the proposed approach of (Zhuang et al., 2018). Similarly, the DT could act as an enhanced 'tracking simulator', where the DT can automatically schedule maintenance of a system, but does not perform real-time control (Werner et al., 2019). Other practitioners use the term 'digital twin' for high-fidelity models which replicate the physical system but do not communicate with it (Miller et al., 2018).

While these three papers do describe 'digital versions' of the real system or product, they are very different in their capabilities. We therefore argue that these practitioners are using the term 'digital twin' in differing ways in their domain, and further analysis and breakdown of the term in each domain is required to understand the real power of the DT paradigm. We propose as a step towards this analysis the identification of fourteen essential characteristics and the construction of a conceptual structure to be used for practitioner's reports about their solutions.

Contribution. This paper's main contribution is the presentation of a conceptual structure to a) offer a summary for practitioners for the description of fourteen essential characteristics of their DT solution, such as the time-scale of operations and fidelity, b) offer a common structure for the description of DT architectures at a conceptual level for practitioners and researchers, and c) emphasize a DT solution as a constellation of modular components to support multiple usages such as visualization or optimization.

This structure is evaluated by expressing in this paper five experience reports from the literature, with a further fifteen reports found online (Oakes et al., 2020). This highlights the applicability of the structure in providing structure for the experience reports to describe essential characteristics of DTs, and how this unclear information can hamper the classification of DT solutions. For example, in six cases a different classification than that of others is suggested.

2 MOTIVATION

This section motivates our proposed conceptual structure by examining a digital twin (DT) experience report for a "human-robot collaborative work environment" (Malik and Bilberg, 2018). This report was selected for its recency, industrial relevance, and complexity.

The experience report domain is an industrial assembly process utilizing plastic and metallic parts to assemble an (unreported) product, where the production is high in volume and the diversity of variants. Assembly is performed using a human-robot collaborative system, combining the flexibility of humans with the efficiency of machines. This collaborative system is challenging however, as any changes to the process requires new analyses for potential collisions between the human and the robot, the workflow itself, and possibly the generation of new robot code.

The report suggests assistance for these analyses using a DT. The data from the factory floor such as the production requirements and inventory is provided to the DT as input. This input is then utilized for DT usages such as visualization, task allocation between humans and robots, workstation layout/ergonomic analysis, and programming the robot. Each usage is enabled through simulation of the assembly task and optimization of various parameters as defined by fitness metrics. The DT then produces workspace planning, a task allocation, and behavioural code for the robot.

Unreported Characteristics We find that essential characteristics about the DT solution are not reported in this report, and there is precision missing which would be valuable to characterize this DT and provide a basis for further research.

For example, the *time-scale* of the DT solution is not clear as regards to each DT *usage*. As described in Section 3.3.4, the time-scale of a DT activity could be classified into *slower-than-real-time*, *real-time*, or *faster-than-real-time* (utilizing predictive simulations). The experience report describes real-time data flowing into the DT, however all of the DT usages are described as "off-line". Therefore it is not clear if the DT utilizes predictive simulations employing this real-time data as it comes in, or whether the real-time data is simply a source of metrics for the off-line simulations triggered when production parameters change.

Section 5 of the paper also mentions "real-time performance metrics, optimization analytics and alerts for a robot" supported by a commercial robot analysis tool. It is therefore not clear whether the DT produces *insights* into the assembly workstation (such as a status dashboard) based on this real-time data, or whether it is only receiving the data for use in manually-activated simulations and optimizations.

Difficulties with Classification As described in the introduction, this precise information about the DT activities can be crucial for researchers and practitioners to classify the DT solutions appropriately. For example, while the DT solution in the report is discussed as a *digital twin*, it is classified as a *digital shadow* by (Fuller et al., 2020). They rely (as we do) on the classification of (Kritzinger et al., 2018) who specify that the distinctive characteristic of a *digital twin* compared to a *digital shadow* is the automatic flow of information from the digital object to the physical object. In our reading of this experience report, the distinction between *digital shadow* and *digital twin* for this report comes down to whether there exists an automatic procedure for adaptation of controller code for the robots based on workstation conditions. If there is an *automatic action* as described in Section 3.2.1, then their solution may yet be a *digital twin*, but it is unclear from the paper whether such a procedure exists. This omission about the characteristics and capabilities of the DT solution affects the classification by not only Fuller *et al.*, but also (Uhlenkamp et al., 2019) who distinguishes between manual, semi-automated, and automated *data integration*. We therefore claim that having structured information about the reported DT solution would resolve this classification issue and could lead to further valuable insights into DTs. This is demonstrated in Section 3.5 by summarizing the main characteristics of this experience report.

3 DESCRIBING DIGITAL TWINS

This section focuses on our main contribution: an organizational structure to describe digital twins (DTs) and their relation to a system-under-study (SUS). First, we present this relationship and a few key aspects. Second, we emphasize that DTs support multiple usages by describing collections of supporting components. Finally, we summarize essential characteristics of DTs, such that practitioners can report the full details and capabilities of their solutions so that they may be precisely classified and understood.

The basis for our conceptual structure and selected characteristics are a selection of experience reports in the literature (Oakes et al., 2020). The reports are inconsistent in the level of detail they report for their DT solution characteristics, but most report these selected characteristics, if only briefly. Thus, from this commonality we claim that these characteristics are essential for high-quality reporting of a DT solution.

Relating Digital Twins to the System-Under-Study The core of the DT concept is the relationship between the DT and the SUS as visualized in Figure 1. The DT is a black-box system in this figure as it is further explored in Section 3.3.

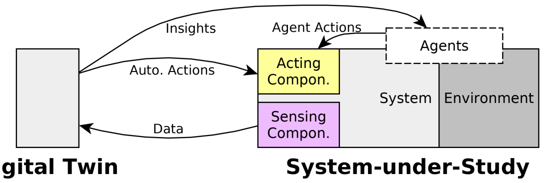

Figure 1: Digital Twin and the System-Under-Study.

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3.1 System-Under-Study

As with any modelling activity, the SUS is the central focus of the entire activity (Zeigler et al., 2000). In our conceptual structure, the SUS includes not only one particular entity (*system*) or set of interacting entities, but also the context (or *environment*) of these entities. For example, the system may be an aeroplane (composed of software, signals, mechanical components, etc), along with the influencing factors of its environment (wind forces, temperature, etc.). As DTs originate in the product manufacturing domain, the SUS is commonly a realized physical system. However, our structure and terms are applicable for either a physical or virtual SUS.

The human or artificial intelligence (AI) *agents* operating within this SUS may also be relevant to what is considered the SUS by the practitioner with respect to the DT. This is denoted in Figure 1 by the dashed extension box. An example of these agents may be aeroplane pilots who interact with the controls, or an AI agent scheduling job allocations in a manufacturing process.

Our assumption is that the DT practitioner has properly scoped their SUS to determine what is relevant for the DT. As in, it is clear what is in the system and the environment, and whether any agents are part of the system (as in healthcare applications (Liu et al., 2019)), the environment, or outside of the SUS entirely. This division is a highly complex part of any modelling activity as it requires expert knowledge on the properties of interest of the SUS and their influencing factors (Zeigler et al., 2000). Only the practitioner can reason about and decompose their system (or system-of-systems), therefore we group this collection of system, environment, and (possibly) agents under the term 'system-under-study'.

Figure 1 emphasizes the conceptual separation of the DT and the SUS. In practice, they may be intertwined as a DT could be embedded into the SUS as a controller of system behaviour. In this case, the DT and the SUS influence each other by competing for processing or memory resources or through temperature effects.

3.1.1 Acting and Sensing Components

Implementing a DT of a SUS may necessitate modifications to the SUS to support the (uni- or bi-) directional information connection between the DT and the SUS (Chhetri et al., 2019). Our conceptual structure specifies that practitioners should highlight the (interesting) *acting* or *sensing* components of the SUS which support this connection to the DT, as this could help researchers and practitioners understand the cost and effort required to connect a SUS to a DT.

Acting components enable control over the system by the DT. These components receive (automatic or manual) *actions* from the DT and agents, and perform some actions on the SUS itself. For example, a Programmable Logic Controller (PLC) embedded within a manufacturing machine may adjust digital parameters or physical actuators.

Sensing components obtain and transmit data for the DT. For example, this may be a humidity sensor connected to a radio network, or the addition of a Product Life-cycle Management system to store product data (Tao et al., 2018a).

The division between these acting and sensing components, and the underlying SUS is (necessarily) blurry. For instance, these components are part of the SUS as they may have direct effects on the system itself, such as power draw, temperature effects, etc. These components may also exist as part of the original SUS and be repurposed for the DT activity. In any case, as these components are essential to support the DT activity, they must also be considered part of the DT solution. The exact separation may not be of consequence, but the experience report should explain their interactions precisely.

3.2 Connection

The connection between the DT and SUS forms the backbone of the DT activity (Grieves and Vickers, 2017). For example, a change in state or behaviour in the SUS is reflected in the DT, or an action commanded by the DT is communicated to the SUS to be acted upon, as represented by the bridging arrows in Figure 1.

The characteristics of this connection is the defining feature which separates a digital representation into a *digital model*, *digital shadow*, and *digital twin* as defined in (Kritzinger et al., 2018). As a recap, if there is no automatic information flow from the SUS towards the digital representation (e.g. no "live" data from the system), the digital representation is a *digital model*. If there is no automatic information flow from the digital representation towards the SUS (e.g. no actions commanded on the SUS), then the digital representation is a *digital shadow* or "tracking simulator".

3.2.1 Data, Insights, and Actions

The data, insights, and actions in this connection depend on the precise DT activities.

Data is any information, such as sensor data, flowing from the SUS to the DT. This data flow may be automatically performed, or entered into the DT solution manually.

Insights are actionable pieces of knowledge obtained about the SUS by utilizing the DT for reasoning. These insights are then be transmitted to agents who may (or may not) provoke a change in the SUS, such as system designers or engineers. For example, a factory's geometry and worker behaviour could be simulated such that insights would be used to provoke the designers to modify the factory layout (Zhuang et al., 2018).

Automatic actions are those commands sent by the DT to directly modify the SUS, such as automated control signals to direct SUS components ordered by the DT (Min et al., 2019). *Agent actions* are those where the agents provoke a SUS change either physically or digitally.

Based on the classification of (Kritzinger et al., 2018), our conceptual structure specifies that only when there is automatic *data* flowing from the SUS to the DT, and automatic *actions* flowing the other way, that the digital solution is a true *digital twin*. That is, there must be a two-way automatic connection between the DT and the SUS.

3.2.2 High-Fidelity

A crucial aspect of this connection between the DT and the SUS is its level of *fidelity*. Clearly, the DT must have "sufficient fidelity" and (adequately) reflect the state and behaviour of the SUS. For example, (Zhidchenko et al., 2018) create a simplified model to predict the trajectory of a mobile crane. The goal is to balance simulation of the model in real-time against the approximation of complex reference behaviour.

However, the fidelity between the DT and the SUS cannot be summarized broadly. Instead, this fidelity is defined only with respect to the particular *usage* (or usages) of the DT (cf. Section 3.3.1), for the properties-of-interest relevant to that usage. For example, if the usage of a DT is the visualization of a factory for training purposes, then only the geometry and colours of the factory may need to be represented at a relatively coarse level of precision, and not the humidity of the air.

It is therefore more precise to state that the DT must have sufficient fidelity to the SUS for the properties relevant to each of the DT's usages. That is, the DT must adequately reflect the current state of the SUS for those properties (at least). If this is not the case, the DT cannot support that usage and cannot provide the required insights and actions, and therefore fails as a "mirror" of the SUS (Worden et al., 2020). This lack of fidelity could occur when a practitioner has not sufficiently defined the influencing factors on the system and modelled them appropriately in the DT (Traoré and Muzy, 2006).

Our emphasis on fidelity with respect to the usages of a DT is to steer practitioners away from defining any *high-fidelity model* as a DT. This is not sufficiently precise as a model has only high fidelity *with regard to certain properties-of-interest*. These properties arise through the analysis and modelling of the SUS (Zeigler et al., 2000) and are related to the usages of the DT.

3.2.3 Multiplicity

Our conceptual structure requires that the multiplicity of the relationship between the SUS entities and the DT be explicitly specified to understand a) what are the entities in the SUS that the DT is reasoning about and operating on, and b) how many DTs are present that obtain information on and influence the SUS. The establishment of the information flow of insights, actions, and data can only be accomplished if there is a *many-to-one relationship* of DTs to the SUS. In other words, a DT must be connected to exactly one SUS for the system's scope to be properly determined.

For example, consider a system of flying drones. A DT could be constructed for each individual drone, which takes data from that drone and provides insights or actions. Thus a group of DTs is created where each DT is connected to a particular drone, termed a *DT Aggregate* by (Grieves and Vickers, 2017). Another approach is to build a DT where the SUS is the swarm of drones itself, or the statistical measure of the "average" or "typical" drone. That is, data from all drones is collected at one central DT and actions are sent to the swarm as a conceptual collective to control the individuals. These approaches would be selected based on the available resources and system design.

3.3 Digital Twin Layers

Our conceptual structure decomposes the DT itself into three sections: a) the *usage* of that DT, b) the *enabling components* for that usage, and c) the *models and data* used by those enabling components, as seen in the *DT Instance* in Figure 2. This division serves to a) offer practitioners more structure in describing their DT solution, and b) emphasize the modular nature of DTs and how *slices* can be created to support different usages.

3.3.1 Usages

The *usage* of a DT is the purpose with respect to the SUS, where benefit is brought (directly or indirectly) to the SUS. For example, a DT may

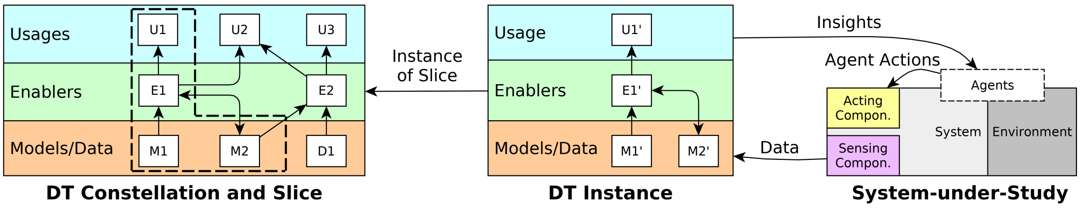

Figure 2: An overview of our conceptual structure for describing digital twins.

monitor the SUS and command modifications to SUS parameters as a usage of *process optimization*, or for *visualization* for design or for training maintenance workers on different scenarios. A third usage is for *anomaly detection* where the DT tracks the system to perform safety actions when the system is outside of its safe operation range. (Tao et al., 2018a) present further usages for product design throughout the life-cycle stages.

In our conceptual structure, a particular DT is restricted to supporting exactly one usage. Section 3.4 discusses a DT structure for multiple usages which we term a *constellation*. This restriction of a DT to one usage scopes the description of that usage's data requirements, insights and actions, time-scale, and fidelity considerations. Providing this granularity allows researchers and practitioners to better understand the cost-benefit impact for adding new usages to a DT solution.

3.3.2 Enablers

The *enablers* are (conceptually) below the usages, and are those components of the DT that operate on the models and data in the DT and directly enable a usage. This definition for enablers is intentionally broad to support many types of components serving usages across different DT domains. For example, (Werner et al., 2019) discuss how a predictive maintenance usage is enabled by a state predictor/simulator based on machine metrics. A video game engine like Unity (https://unity.com/) enables virtual spaces for visualization of personal health metrics (Mohammadi and Taylor, 2020).

3.3.3 Models and Data

Finally, the *models and data* used by the DT are grouped together on a (conceptual) layer and are both input and output for the enablers. For example, data could be input into a machine learning trainer (an enabler) to produce a neural net (a model) (Min et al., 2019).

3.3.4 Time-Scales

An essential characteristic of DTs is that the communication between the SUS and the DT for a usage most likely occurs at different time-scales. A usage's insights, actions, and data communication could each occur as *slower-than-real-time* or *real-time*, and the usage itself could rely on *slower-than-real-time*, *real-time*, or even *faster-than-real-time* reasoning.

If an insight, action, or data collection step is *slower-than-real-time*, that part of the cycle is not real-time "live" but instead the DT periodically receives data from the SUS, or issues insights or action to the SUS for some future time. For example, a predictive maintenance DT could receive real-time machine sensor information, but issue insights to a scheduling agent to modify worker routines for a later shift (Werner et al., 2019).

A *real-time* time-scale is where the action or data collection is communicated between the SUS and the DT for reasoning and provoking of an action on the SUS within a short-scale (most likely sub-second) time-frame. All examples of real-time control by a DT include this time-scale, such as production-time control (Zhuang et al., 2018).

Finally, the *faster-than-real-time* time-scale is where the enablers for a usage perform predictive simulation to predict the state of the SUS in the (near-)future. This faster-than-real-time simulation is then used to produce insights and actions, such as slower-than-real-time insights or actions like workstation layout modifications (Malik and Bilberg, 2018), or real-time trajectory optimization for crane control (Zhidchenko et al., 2018).

The collected examples in Section 4 (and online (Oakes et al., 2020)) demonstrate how a DT solution most likely involves communication at all three time-scales. The time-scale characteristic of DT communication is explicitly expressed in our characteristics, as practitioners could have the belief that a "true" DT is only those that have "hard real-time" control connections. We leave this particular interpretation open for now, but our conceptual structure provide the guidelines for experience reports such that future research can discuss classifications in each practitioner domain.

3.4 Constellations and Slices

One benefit of DTs is that once there is a critical mass of high-quality enablers, models, and data, then multiple usages become possible (Uhlemann et al., 2017). Our conceptual structure denotes a DT *constellation* as an agglomeration of all related models, data, enablers, and usages that are used in the DT activities involving a particular type of SUS, as shown on the left-hand side of Figure 2.

A particular enabler may support multiple usages within a constellation, and a model or piece of data may be operated upon by multiple enablers. For example, in Figure 2, enabler *E1* supports usages *U1* and *U2*, while enabler *E2* supports usages *U2* and *U3*. Figure 3 presents a constellation for the experience report in Section 2.

A DT *slice* is then the selection of components in a DT constellation to support a particular usage. For example, in Figure 2 one out of a possible three DT slices is represented by the dashed lines around the components which support usage *U1*. This slice can then be implemented by any number of *DT instances*, as represented in the middle of Figure 2, where prime marks denote an instance of a slice. These slices therefore reinforce the modular nature of DTs, where the enablers and models and data are reused for multiple usages within a DT constellation.

Note that the DT constellation and DT slice are conceptual objects to group components of the DT activity for description purposes. Constellations and its slices likely do not exist either physically or virtually in the practitioner's DT solution. In contrast, the DT instance must be running on a computational device, and the connected SUS must exist in the physical or the virtual world.

3.4.1 Life-cycle Stages

DTs in the literature operate at various stages in the life-cycle of a system. These stages are not fixed and have domain-specific terms such as *design*, *pre-production*, and *production* (Söderberg et al., 2017), or *ideation*, *realization*, and *utilization* (Leinen, 2017). (Pokharel and Mutha, 2009) also consider a *reclamation* life-cycle stage, involving disassembly and re-use in new products.

As the SUS moves through the stages of its life-cycle, the usages of its connected DTs and the scope of the SUS will likely change. For example, during the ideation phase a DT may offer optimization and visualization usages for product design (Tao et al., 2019). During later stages, the SUS may then expand to encompass the manufacturing facility and worker's routines, where the optimization usage must then consider new objectives and parameters (Söderberg et al., 2017).

Our conceptual structure thus suggests a report of a DT solution includes the usages and scope for the SUS (if different) for each of the life-cycle stages in the solution. This assists researchers and practitioners in classifying their DT solutions, identifying challenges, and recommending useful enablers for each life-cycle stage. For example, assembly and disassembly processes for a product may share enablers provided by a DT solution.

3.4.2 Evolution

As practitioners build up techniques and tools and discover new DT requirements, the solution and its constellation evolves to support further usages across the life-cycle stages, and between different product versions. For example, (Söderberg et al., 2017) report seven DT usages spread across three phases of the product life-cycle but not the order of their development.

Providing information on the evolution of the constellation could enable further classifications and research insights into DTs. An example could be identification of whether the *digital model* (Kritzinger et al., 2018) used in the design stage is often first transformed into a *digital shadow* (as in (Min et al., 2019)), or whether it is directly used as the basis for a *digital twin*. Another example would be scheduling the implementation of design-stage usages in parallel with the pre-production and production stage usages.

3.5 Essential Characteristics

This section provides a summary of the essential aspects of our conceptual structure to provide a structured list for the precise reporting of DT characteristics in future experience reports.

We present here brief details from the collaborative assembly experience report detailed in Section 2. This demonstrates that even with a high-quality report, there are still characteristics that remain unclear such as the time-scale of certain insights and actions, as denoted with a question mark. As discussed in Section 2, these missing details hamper the classification and capabilities of this experience report.

Due to space reasons, only the briefest sketch of relevant details is presented here. This summary is far less than the level of detail we expect practitioners to provide in their experience reports.

System-under-study - *The scope of the SUS including the system, environment, and agents.* A collaborative assembly process, involving humans,

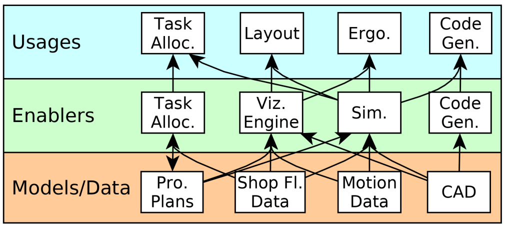

Figure 3: A possible DT constellation for (Malik and Bilberg, 2018).

robots, workstation, an assembly station, production steps, and product parts.

Multiplicities - *How many DTs and SUS entities are involved in the solution, and their relationship.* DT instances exist for each workstation in the assembly process.

Usages - *The activities the DT is used for.* Task allocation between humans and robots, layout generation for the workstation, ergonomic analysis, and robot code generation.

Enablers - *The DT components which use models and data to support usages.* A visualization engine for the layout usage, task planner for allocation, workstation simulator, code generator for robot programming.

Models and Data - *The input and output for enablers.* Computer-aided design (CAD) models for human, robot, and workstation, motion data from three-dimensional camera, shop-floor data (inventory, etc.), production plans.

Slices - *Relationships between usages, enablers, and models and data.* Our impression of the DT constellation for this report is seen in Figure 3.

Fidelity Considerations - *Explanations of fidelity of DT to SUS with respect to each DT usage.* For layout and ergonomic usages, workstation and robot geometry must be accurate within a few millimeters(?). Human model corresponds to a typical Danish worker. For task allocation usage, shop floor data has slight variations(?).

Data Communicated - *What is transferred from SUS to DT.* ***Manual:*** Production requirements(?) ***Auto:*** Inventory data, robot data.

Insights and Actions - *What is communicated from DT to SUS.* ***Insights:*** Task allocations, workspace layout, assembly procedure and configuration. ***Actions:*** Robot code(?).

Time-Scale - *The time-scale of the data, insights, actions, and simulations used.* ***Slower-than-real-time:*** Production requirements, task allocations, workspace layout, assembly procedure and configuration, robot code. (Unclear, could be real-time on “production changeover”) ***Real-time:*** Inventory and robot data. ***Faster-than-real-time:*** Task allocation and ergonomic usages.

Acting Components - *Add./modif. to SUS enabling DT actions and insights.* Not reported.

Sensing Components - *Add./modif. to SUS enabling DT data collection.* Not reported.

Life-cycle Stages - *The stages of the life-cycle that the DT is utilized for, the usages for each, and (if varying) the scope of the SUS.* ***Design:*** Task allocation, workstation layout, ergonomic analysis. ***Development:*** Workstation layout (?). ***Operation:*** Task allocation, workstation layout, ergonomic analysis, code generation.

Evolution - *How the DT evolves over the DT project timeline.* Visualization developed, then event-based simulation.

3.6 Threats to Validity

A major threat to validity of our conceptual structure is whether the fourteen characteristics we have presented here are essential for practitioners to communicate in their experience reports. This threat has been addressed by selecting those common characteristics which were discussed (at least briefly) in the considered experience reports in the literature (Oakes et al., 2020).

A related threat is the applicability to DTs in different domains, and that it is insufficiently detailed enough for practical usage. This threat is partially addressed by providing examples of the conceptual structure’s usage for multiple experience reports, both in this paper and online (Oakes et al., 2020). The conceptual structure is also at a general level, including broad characteristics such as *enablers* and *models and data.*

Our selection of relevant characteristics will never be sufficient for all domains, as many other dimensions are relevant for stakeholders in particular domains. A few examples include the particular technology solutions used, the business case and stakeholders for each usage, or cybersecurity considerations. It is therefore our hope that researchers and practitioners will use our conceptual structure as a starting point, and eventually coalesce around a particular set of defined characteristics for each individual DT domain.

4 APPLICATION EXAMPLES

This section examines four selected works from the literature described as digital twins (DTs), using our conceptual structure to produce a table of characteristics (Table 1). This section is to demonstrate applicability to DT solutions in multiple domains, and highlight how this structure ensures that these characteristics are reported to assist with further classification and insights. As a visual guide, missing entries are marked in bold, while unclear information is marked in italics. Similar to Section 3.5, only the briefest of details are reported here due to space considerations.

Boat Avatar (Wuest et al., 2015) describe a "product avatar" approach where the information from sensors on leisure boats is used to provide services to manufacturers and boat owners. For example, maintenance information is collected during the winter season when boats are in storage, and service offers are relayed to service providers and boat owners to offer repairs or refurbishment.

(Uhlenkamp et al., 2019) identifies this experience report as a "digital twin application scenario". However, this report is difficult to classify according to (Kritzinger et al., 2018) as it mostly describes a *digital shadow* where no automatic actions are commanded. We have identified one possible action: boat information could be automatically posted to social networks. Further clarification by the authors is therefore required to classify the DT solution as a *digital twin*.

As well, it is difficult to understand the precise system-under-study (SUS), insights, and actions involved. In particular, in Table 1 we have placed the boat manufacturers and the boat owners as *agents* and as part of the SUS, but this may not be the intention of the report authors.

Cyber Guided Vehicle (Bottani et al., 2017) detail the creation of a simulation for an Automated Guided Vehicle (AGV) in the context of a job-shop where the AGV transports materials to be assembled. The same code from the AGV runs inside the simulation, which is used to optimize the AGV's policies for maximum profit.

This report also lacks relevant details about the DT solution. In particular, Table 1 in (Kritzinger et al., 2018) claims that this solution is a *digital twin*. However, from our reading the only communication between the digital object and the physical AGV would be the policies or AGV code. It is unclear whether this communication would be automatic to and from the AGV to the digital object and how often this would occur. This experience report may thus describe a *digital shadow*.

Oil and Gas Drilling (Mayani et al., 2018) report the successes of using DT technology by a Norwegian oil and gas technology provider. Four uses of the DT technology at three oil and gas wells for monitoring and training purposes are discussed, as well as the cost- and time-saving benefits. As drill parameters are optimized based on the digital object, the overall solution is a *digital twin* by the classification by (Kritzinger et al., 2018). However, the training usage of the solution may not lead to automated control actions with the SUS, thus indicating that the DT solution acts as a *digital shadow* for some usages.

Petrochemical Optimization (Min et al., 2019) provide an excellent report on the use of digital twins for optimization of petrochemical production. Data from factory sensors undergoes cleaning such as time series unification, before it is used alongside historical data for machine learning training and prediction. The DT solution determines recommendations and control actions to improve the economic potential of the plant, such as by increasing the yield of light oil.

As this report explicitly mentions the use of control actions on the plant, our reading suggests it is a *digital twin* as per the classification by (Fuller et al., 2020). However, this report is classified as a *digital shadow*, possibly due to the ambiguous sentence "[the output], real-time recommended control information, is viewed by operators first before being utilized in the production system". It is therefore not clear if the control information is presented as insights, or is an action on the system. The capabilities and classification of this DT solution would therefore be clarified when presented in our conceptual structure.

5 RELATED WORK

Structured DT Definitions

(Grieves and Vickers, 2017) define DT Prototypes, DT Instances, and DT Aggregates. DT Prototypes exist only in the design stage of a system, before being realized as a *Physical Twin*. Each Physical Twin is then monitored and acted upon by a DT Instance. A collection of DT Instances is a DT Aggregate. This structuring parallels our own, where DT Prototypes would be the models and data involved in a DT Constellation while the DT Constellation operates in the design stage of a system. The concept of the DT Instance is the same as a particular instance of a DT communicates with a system-under-study (SUS). Our structure requests that the multiplicity of the DTs with relation to the SUS be explicit for clarity, such as whether multiple DT instances are aggregated to form a DT of a larger system.

(Tao et al., 2018b) present a five-component structure for relating DTs and the SUS: a) the *physical entity model* which is the SUS including sensors and actuators, b) the *virtual equipment model* including models and behaviour description, c) a *services model* with the *usages* of the DT and

Table 1: Four digital twin experience reports as presented in our conceptual structure.

Expr. Report	Boat Avatar (Wuest et al., 2015)	Cyber Guided Vehicle (Bottani et al., 2017)	Oil and Gas Drilling (Mayani et al., 2018)	Petrochemical Optimization (Min et al., 2019)
System-under-study	*Leisure boats and stakeholders (owners, manufacturers, social networks) (?).*	Auto. guided vehicle (AGV) in job-shop prod. system.	Performance of and forces on drilling rig.	Catalytic cracking unit in petrochemical production line.
Multipl.	DT instances per boat.	DT instances per prod. system.	DT instances per drill site.	DT instances per unit.
Usages	Optimizing design/production, enhancing boat experience, upgrade services.	Optimizing policy for system profit, visualization.	Planning, training, operation forecasting.	Production optimization.
Enablers	Production decision support, web presence, maintenance recommenders.	Simulator, AGV controller.	Sim. of performance and forces, auto. monitoring.	*“Profit and market modelling systems”, “sim. and opt. systems”, machine-learning algs.*
Models & Data	Data from boat, predictive models for maintenance recommenders.	Model of shop, AGV code, prod. data.	Sensor data, hydraulic and mechanical models.	Machine learning models, historic data.
Slices	[Omitted for space]	Same slice for usages.	[Omitted for space]	*Unclear.*
Fidelity Consid.	*Realistic for optimizing and services, less realistic for boat experience. Not explicit.*	*Realistic for optimization, less realistic for viz. Not explicit.*	*Highly realistic for planning and forecasting, realistic for training. Not explicit.*	Realistic. Data must be cleaned and aligned before processing.
Data Comm.	Auto: Assorted boat conditions, such as battery/fuel level, current weather, maintenance status, position, etc.	*None (possibly code?).*	Auto: Temperature, pressure, etc.	Production plans, production line data.
Ins. & Act.	*I: Boat info., service recommendations & offers. A: Posting to social networks(?).*	*I/A(?): AGV controller code.*	I: Performance reports. A: Drill control signals.	*I: ”Analysis data” and recommendation info. A: Control instructions.*
Time-Scale	*Slower-t-r-t insights, real-time data, real-time posting to social networks (?).*	Slower-t-r-t.	*Slower-t-r-t for reports & training, real-time for control, faster-t-r-t for sim.(?).*	Slower-t-r-t historical data and insights, real-time data and control actions.
Acting Compon.	Created web platform integration.	**No compon. additions reported.**	**No compon. additions reported.**	*“Industrial IoT systems”, such as “electric and electronic circuits”*
Sensing Compon.	Product Life-cycle Management system, data integration layer	**No compon. additions reported.**	**No compon. additions reported.**	Measuring instruments, “sampling, preprocessing and injection systems”, monitors and recorders.
Life-cycle Stages	*Ideation, realization, utilization, reclamation. SUS: No manufacturers in middle stages (?).*	Utilization.	Ideation, realization, utilization.	Utilization.
Evolution	Usages created, then data connection, then insight/action connection.	**Not reported.**	*Used for training, then used for control(?).*	Basic DT constructed, then trained on existing data, then connected to SUS.
Class.	DS/DT (?)	DS/DT (?) (versus DT by (Kritzinger et al., 2018))	DT	DT (versus DS by (Fuller et al., 2020))

include quality information, d) a *DT data model* to structure the domain knowledge of the DT, and e) a *connection model* which structures the incoming or outgoing data from the DT, such as variable type and sampling interval. In contrast, our structure is at a higher level of abstraction and is not about technical details but only a summary of the characteristics and capabilities.

Further work by (Tao et al., 2019) focuses on the use of DTs for product design and manufacturing, such as enabling technologies for DTs and a 'V-cycle' for validating and verifying product design. Also relevant is the investigation of the steps of *building* the DT for product design, which is similar to our concept of *evolution*. These steps involve the creation of the virtual product and its connection with the physical product, where the DT solution moves from a *digital model* through a *digital shadow* stage to become a *digital twin*.

(Worden et al., 2020) take a mathematical approach to DTs where *mirrors* are defined which replicate the behaviour of a system in an environment and context according to a fidelity measure. These *Turing mirrors* must provide the same answers to questions as the original physical system. This is relevant to our work as it formalizes our *fidelity* characteristic.

Digital Twin Aspects/Characteristics

(Boschert and Rosen, 2016) discuss the use of DTs for simulation throughout a system's life-cycle stages and the need for DTs to be modular to fit into *value chains*. The DT *purpose* may also change due to the current life-cycle stage of the system or the maturity of the DT itself.

Similar to our work, (Uhlenkamp et al., 2019) present seven characteristics of DTs. *Goals* refer to the abilities of the DT and include *information acquisition*, *information analysis*, *decision and action selection* and *action implementation*. *Users* focus on one user or multiple stakeholders. *Life-cycle focus* can likewise be a single stage or multiple. A *system focus* can be *component*, *subsystem*, *system*, or *system of systems*. *Data sources* for a DT include *measurements*, *virtual data* (including simulation data), and (expert) *knowledge*. *Data integration levels* replace the classification of (Kritzinger et al., 2018) with *manual*, *semi-automated*, and *automated*. Finally, their characteristics include *authenticity* which we refer to in our conceptual structure as *fidelity*. While relevant, we demonstrate in Section 2 that further characteristics and detail may be required in current experience reports to apply their structure.

According to (Madni et al., 2019), DTs are an enabling technology in the next steps of *model-based system engineering* (MBSE). A comprehensive examination of DTs within the context of MBSE is presented, along with a classification of DT maturity throughout the life-cycle of the system of *pre-DT*, *DT*, *adaptive DT*, and *intelligent DT*. Relevant to our work is a list of characteristics which separates DT from traditional *computer-assisted design* (CAD) models, including *specificity*, *understanding assumptions and performance*, and *traceability* among others.

(van der Valk et al., 2020) propose a DT taxonomy with characteristics and relationships, while (Jones et al., 2020) details a literature survey. These works propose further characteristics of DTs, but do not create a conceptual structuring.

6 CONCLUSION

This paper presents a conceptual structure for describing digital twins (DTs) such that practitioners can structure their reporting and ensure they describe essential characteristics and capabilities in their experience reports. In turn, this provides a firmer foundation for the DT research community to gain further insights into challenges and solutions, and offer a more precise classification of the DT types in practice. It is our ambition that this structure serves as a common reference to enable clear communication of DT solutions between academic and industrial stakeholders. The applicability of the structuring and its use in structuring a report and indicating missing characteristics has been demonstrated by expressing multiple experience reports from the literature. This has revealed six cases where the suggested classification differs from that of others (Oakes et al., 2020).

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