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A MULTI-DIMENSIONAL DIGITAL TWIN USE CASES CLASSIFICATION FRAMEWORK

Ramy Al-Sehrawy*, Bimal Kumar, Richard Watson
Department of Architecture & Built Environment, Northumbria University, UK.
*Corresponding Author

ABSTRACT

The concept of a Digital Twin [DT] has been gaining increasing attention in the realm of urban planning and city infrastructure management. In support of this movement, DT advocates have been consistently casting light on the possible DT use cases to better manifest its potential and the enormous value it promises to unlock. However, these attempts are arguably limited by the lack of a formal and standard DT use cases classification framework. Hence, this paper puts forward a multi-dimensional DT use cases classification framework, based on published key DT case studies and a framework development methodology, to address this limitation. It concludes with insights on further possible implications of, and enhancements to this framework.

INTRODUCTION

Al-Sehrawy and Kumar (2021, p.926) described a DT as “the concept of connecting a physical system to its virtual representation via bidirectional communication (with or without human in the loop)… [allowing] for exploitation of Artificial Intelligence and Big Data Analytics… to unlock value”. Accordingly, in a broader sense, a DT for urban planners and city infrastructure managers is primarily concerned with leveraging urban data to support decision making with the aid of new generation IT tools.

As the idea of DT strives for wider adoption to support decision making in urban environments, many DT researchers and practitoners are interested in enumerating and grouping the so-far known DT use cases (Brilakis et al. 2019; IET, 2019) in an attempt to demonstrate the value of DT and highlight its potential in cutting through a diverse range of fields across the realms of urban planning and city infrastructure management. However, such endeavors have been largely ad-hoc with no clear framework or a-priori set of standard criteria to aid in the process of categorizing or classifying these use cases. Besides, this problem will get more severe once DT implementation proliferates giving rise to new use cases; thus, ending up with more available use cases begging for some sort of formal standard classification.

This paper proposes a standard multi-dimensional classification framework of DT use cases, taking into account key features or aspects that may distinguish one use case from another. This framework provides means for classifying any DT use case via a multi-dimensional classification system. The value of this calssification framework is twofold. On one hand, it can help DT owners to better define, refine and clarify any proposed DT use case at the outset of a project based on a set of standard criteria that acts as a common language amongst stakeholders to avoid ambiguity. One the other hand, it can also enhance the DT practitioners’ ability to consistently relate, draw parallels or compare between different DT use cases based on the same classification criteria and DT key features. The following three sections explain the methodology adopted in developing the framework; provide a detailed account of the framework and each of its dimensions; and finally conclude the study.

METHODOLOGY

A framework development methodology of three stages is adopted to develop the DT use cases classification framework (McMeekin et al., 2020), viz. (a) Data Extraction: A total of 580 studies were found after searching online databases using a combination of a set of keywords, including City; Urban; Infrastrcture; Digital Twin, Smart City, Big data; Data-driven; and Planning. First, Studies retrieved were eligible for inclusion if found to satisfy the following a-priori set criteria: (i) they are in the English language; (ii) published from 2017 onwards; and (iii) including either an empirical case study demonstrating a DT in action, or a methodological approach proposing how a DT can be built or a DT use case is classified or realized. Titles and abstracts or the introductions of returned documents were screened to identify those deemed potentially eligible and those which can be immediately excluded based on our definition of DT. Duplicates and full-text dissertations were removed. (b) Synthesis: involved qualitative content analysis of 89 potential studies retrieved from literature to identify key characteristics of DTs built. (c) Development: identified features are grouped and aggregated into fundamental standard dimensions constituting the DT use case classification framework as one integral whole. Stages (b) and (c) were conducted in an evolving iterative manner.

Figure 1: 7-Dimensional DT use case classification framework

DT USE CASES CLASSIFICATION FRAMEWORK

Framework structure

Figure 01 illustrates the DT General Use Case [GUC] multi-dimensional classification framework, comprising at the center the purpose of the particular GUC of interest, ideally and plainly articulated in the form of a 'verb' followed by a 'noun' (e.g. optimize traffic), surrounded by seven distinct dimensions representing the various features based on which different GUCs can be distinguished and classified. As this section proceeds, we shall further elaborate on each of the seven dimensions and how each dimension is capable of classifying the DT GUC at focus from a unique perspective in terms of an inherited set of criteria.

D1: Application area

Though still in its nascency for urban planning and city infrastructure management, DT has courageously cut through a diverse range of applications targeting purposes that are worlds apart in terms of scope. Below is an overview of each area of scope, including exemplars drawn from reviewed literature demonstrating ways of how DT tackled each of them.

(1) Futures planning: concerned with long-term planning, futures studies and strategic forethought. In such manner, Anejionu et al. (2019) deployed a DT to identify urban areas of low livability in order to inform the planning for future infrastructure development works. Kourtit and Nijkamp (2018) generated urban performance indicators to support strategic decision making. Pettit et al. (2018) developed a DT to help in the allocation of residential land in 2051. Nochta el al. (2020) created a city DT to plan for the expected patterns of private car use in 2031 to ensure sustainable growth.

(2) Asset management: The scope of work here is more about operating assets and maintaining proper level of service. To this end, Nallaperuma et al. (2019) integrated heterogenous datasets to differentiate recurrent from non-recurrent traffic incidents and simultaneously forecast traffic flow and optimize operation and control decisions. Similarly, Witteborg (2021) explicated how DT may support the smart operation of complex wastewater facilities.

(3) Risk and Resilience management: DTs have shown a capability to support managing risks in infrastructure domain and help enhance assurance for urban environment. White el al. (2021) used a DT to simulate floods, while Bartos and Kerkez (2020) modeled the urban stormwater network in real-time. Likewise, Wang et al. (2020) exploited the smart rail card ticket data to help protect the safety of urban public transportation. Another study used computer vision to anticipate the risk of heat stress on pedestrians (Mavrokapnidis et al., 2021).

(4) Crisis management: A DT can aid decision making at times of catastrophes and natural disasters. In the study carried out by White el al. (2021), a DT is used to help identify safest routes and locations for citizens and show those which are mostly affected during flooding. Moreover, citizens themselves can use user-tagging indicating whether they are in need of assistance, thus enabling the DT to identify the most vulnerable locations during the disaster. Lwin et al. (2018) proposed an hourly updated DT showing traffic flow magnitude (i.e. population) and direction in order to enhance emergency preparedness. Yabe and Ukkusuri (2019) worked on predicting the returning behavior of evacuees during post-disaster periods. The DT of Pang et al. DT (2020) informs city crisis management decision making amid the spread of a pandemic, that is, Covid-19.

(5) User and Demand management: DTs are capable of managing the users' behaviors and their usage patterns. Leleux and Webster (2018) presented a smart solution in the form of a gamified engagement platform to offer access to energy information and encourage citizens to alter their energy consumption behavior. Other DT initiatives and studies aimed to change the citizens' lifestyle, travel behavior and their choices of transportation means (Connecting Bristol, 2021; Kirdar & Ardiç, 2020). In a similar but indirect way, Balletto et al. (2021) attempt to influence public behavior by better utilizing the city's abandoned assets in order to promote walkability as a viable healthy choice, while Orellana and Guerrero (2019) used crowdsourced urban data to better understand the influence of street networks' spatial configuration on the behavioral patterns of cyclists.

(6) Environmental and Carbon management: A DT promises a variety of solutions when it comes to meeting environmental and carbon targets. Honarvar and Sami (2019) integrated heterogeneous sets of urban data to predict air pollution, mainly with respect to road network traffic dynamics. Another study worked on monitoring and benchmarking the energy consumption of city buildings in real-time which would certainly help realize better environmental performance (Francisco et al., 2020).

(7) Waste management: At a different level, DTs offer novel approaches to waste management. Several studies have exploited new technologies such as IoT and computer vision to monitor the level of waste in garbage cans, aka smart bins, which can then notify the relevant teams when waste should be collected, and possibly suggest optimum driving routes to be followed during the process of waste collection from a myriad of bins across the city (Rao et al., 2020; Aktemur et al., 2020; Jadli & Hain, 2020).

(8) Resource management: This involves identifying the best use of available scarce resources, whether monetary or physical, to realize greatest value. Questions relevant to this area of management can be the sort of questions McHugh and Thakuriah (2018, p.4) raised, like: e.g. where would new infrastructure or transportation service investment deliver greatest benefits? Where is there evidence of dissatisfaction with existing services and resources?". Pertinent use cases may include exploiting DTs to manage human waste, such as sludge used in generating energy. Another possible example is a DT of wind farms, capturing data sensed from wind turbines, analyzed with facts about landscape and current wind to optimize configuration of wind turbines to attain higher levels of energy production (GE Renewable Energy, 2021). IET et al. (2019) referred to the value of DT 'what-if' scenario simulations in supporting more sustainable natural resource allocation.

(9) Asset registration: DT's ability of capturing physical reality is best demonstrated in the idea of asset registration. An exemplar is the 'National Underground Asset Register' project led by the Geospatial Commission in UK. It aims to better map the underground infrastructure assets to deliver strike-less construction and safe working environment. So far, two pilot projects were undertaken; one in London and another in the north east of England (Brammall & Kessler, 2020).

D2: Federation

A DT use case can basically target an individual infrastructure asset, a whole infrastructure system comprising multiple assets and networks; or ultimately an integrated system of systems [SoS] where interdependencies between these infrastructure systems – which have been conventionally seen as independent – be them geospatial, cyber, physical and logical interdependencies (Whyte et al., 2019) – are taken into consideration (ISO, 2018). In the first case, several studies captured infrastructure sub-systems, like basins as a part of the stormwater network (Bartos & Kerkez, 2020); pedestrian routes, road or rail networks as components of the transportation system (Mavrokapnidis et al., 2021; Honarvar & Sami, 2019; Wang et al., 2020; Barmpounakis & Geroliminis, 2020; Nallaperuma et al., 2019); or energy consumption of buildings as an element of those connected to the energy grid. In the second case involving full infrastructure systems, Kourtit and Nijkamp (2018) and Anejionu et al. (2019) considered all means of transportation in developing their DTs. Other projects involved multiple distinct infrastructure systems in one DT (Castelli et al., 2019). It is important to highlight though, that the idea of a SoS isn't a utopian dream, but rather a mere mindset – a systemic way of thinking that can cross the organizational boundaries and dissolve the infrastructure sectoral silos. For instance, it was practically adequate for Aktemur et al. (2020) and Jadli and Hain (2020) to consider the functional interdependency between elements of the waste network (i.e. smart bins) and their location with respect to road network in order to identify the best travel route for waste collection. A recent study by the Centre for Digital Built Britain [CDBB] demonstrates an interesting attempt in using a DT to generate new insights concerned with identifying, prioritizing, and managing infrastructure SoS relationships and interdependencies (Whyte et al., 2019).

D3: Layering

An important characteristic of many DT use cases is the diffusion across different city layers. The fact that most smart city research and urban DTs are interdisciplinary, involving interdependent urban data and models (Ma et al., 2019), reflects the reality of multiple layers inherited in the fabric of cities and urban environment. Many researchers attempted to disentangle these city layers; White el al. (2021) recognized the four levels of terrain, buildings, infrastructure and mobility, whilst Ibrahim et al. (2020) identified five layers including built environment, humans' interactions, transportation and traffic, infrastructure and natural environment.

Similarly, Ma et al. (2019) named five different city domains: transportation, energy, emergency and public safety, social sensing and natural environment. In a review of urban planning needs and urban sensing technologies, Cunningham and Verbraeck (2018) spotted three general conceptual perspectives of the city, including physical and infrastructural, natural resources and political economy. Hence, here we take account of four distinctive city layers: Infrastructure; Built Environment, Socio-economic Environment; and Natural Environment.

Depending on the purpose of a use case, in less common cases, a DT may need not involve more than one city layer, similar to how Rao et al. (2020) and Aktemur et al. (2020) were only concerned with infrastructure layer only. Yet, more frequently a DT may penetrate through multiple relevant city layers. Bartos and Kerkez (2020) included infrastructure along with natural environment, while others considered the interactions between infrastructure and socio-economic layers (Jadli & Hain, 2020; Wang et al., 2020; Barmpounakis & Geroliminis, 2020; Nallaperuma et al., 2019). Some authors alternatively involved varying combinations of three city layers while delivering DT purposes (Anejionu et al., 2019; Honarvar & Sami, 2019; Kourtit & Nijkamp, 2018; Francisco et al., 2020; Mavrokapnidis et al., 2021; Barkham et al., 2018; Mayaud et al., 2019), while others included all four as required within some other applications (Pettit et al., 2018; Yabe & Ukkusuri, 2019).

D4: Spatial scale & resolution

In pursuit of pre-defined GUC and a-priori DT main purpose, a DT may deliver an output that varies in terms of the spatial scale – commensurate with spatial coverage – and resolution (Gardner & Hespanhol, 2018; Kontokosta, 2018).These can be at a national, city, neighborhood or individual levels. Two points should be clarified here, though. First, it is important to distinguish between scale and resolution. For instance, Anejionu et al. (2019) developed a DT that spatially covered the UK (i.e. Nation scale) but supported visualization of livability indicators at a finer, neighbourhood resolution. Second, the finest level, Individual, does not necessarily mean individual human beings, but could be any individual element within a neighborhood. An individual constituent part of the neighborhood can be a building, an infrastructural unit, a natural entity, a point of location, a user…etc. The notion of an 'Individual' element here is akin to that of an 'Intelligent Planning Unit' [IPU] as described by Hastak and Koo (2017, p.3) to be a "well-defined planning unit that can be initiated to achieve any specific purpose".

Few DTs focus only at a neighborhood scale with a neighborhood resolution as well (Panagoulia, 2017). For example, Mavrokapnidis et al. (2021) developed a DT bounded to a specific district to predict the heat exposure on citizens within this district. Nonetheless, various DTs have spatially incorporated full cities, albeit with different levels of resolution. For example, Kourtit and Nijkamp (2018) at best provided no finer resolution than aggregate urban Key Performance Indicators [KPIs] of the whole city, while Honarvar and Sami (2019) tackled the issue of air quality at every neighborhood within the city. Mayaud et al. (2019) assessed the accessibility of different neighborhoods to health care facilities across the city; thus, producing a city-scale DT at a neighborhood resolution. Other high-resolution DTs have captured even finer details than city's neighborhoods. For instance, Barmpounakis and Geroliminis (2020) and Nallaperuma et al. (2019) produced comprehensive information with details about individual vehicles. Some studies introduced DTs to provide information about every single smart bin across the city (Rao et al., 2020; Aktemur et al., 2020; Jadli & Hain, 2020), while others have rather captured city buildings separately (Francisco et al., 2020) and individual 50m x 50m grids (Kim, 2020). When it comes to national scale, Pang et al. (2020) worked on integrating city DTs across the nation to support better prediction of pandemic infection spreading patterns. One of the best DTs under development at a national scale is the UK's National Digital Twin [NDT] currently pursued by CDBB.

D5: Temporality & resolution

Analogous to spatial scale and resolution, the dynamism or the temporality of DT output, as well as its temporal resolution, may both change from a use case to another so as to be fit for purpose (Li et al., 2018). It is crucial to differentiate between three types of DTs with respect to temporality. First are the DTs generating a static output based on input that includes no temporal information (e.g. underground asset register). Second are the DTs fed by a chunk of spatiotemporal data, generating an output of a dynamic behavior, like 4D and 5D simulations, yet based on real-world data rather than mere theoretical estimations or assumptions (Al-Sehrawy et al., 2019). Notwithstanding its dynamic output, this form of a DT is deemed to be offline – lacking live connection with the twinned real physical system and thus, exposed to being outdated by a continuously changing reality if not manually updated on regular basis or whenever deemed necessary. Hence, it can be argued that this type of 'offline dynamic' DTs are only more adequate when twinning slowly evolving systems, such as city spatial configurations which may take decades to exhibit significant changes worth of capturing to feed the DT with. An example is the DT computing urban performance indices and KPIs based on datasets collected from 2012 to 2016 (Kourtit & Nijkamp, 2018). Similarly, Wang et al. (2020) inferred patterns of railway passengers flow from smart card ticket data containing data of passengers entering and exiting stations in 2017. On the contrary, some other real-world systems are naturally in a relentless, rapid and unanticipated change. These kind of systems though, are rather more adequately twinned using our third type of DTs – the type of DTs viewed by the DT maturity spectrum developed by IET (2019) as a relatively more mature type of DTs, which we shall call here: 'online dynamic' DT. This type is tied-up in an enduring connection with the twinned real entity and constantly receiving up-to-date influx of data; thus, can never go obsolete as long as this live digital thread persists. To illustrate, Francisco et al. (2020) relied on IoT technology and smart meters to monitor the energy consumption of buildings in real-time (Rao et al., 2020; Aktemur et al., 2020; Jadli & Hain, 2020; Nallaperuma et al., 2019).

Dynamic DTs, whether online or offline, must demonstrate a level of temporal resolution, indicating the temporal steps or increments by which the DT output changes. Pertaining to temporal resolution, authors have tried to set some sort of objective levels. For instance, Kontokosta (2018) identified four distinct levels of temporal resolutions (i.e. real-time; daily; annual; and decennial), while acknowledging that the DT output may eventually lie anywhere in between these thresholds. Moreover, it is worth stating that the notion of real-time is a flexible one (Wan, Yang & Parlikad, 2019). Whereas only the objective in mind driving our intentions to build a DT is responsible for defining the temporal resolution or the frequency by which data generated from a physical system gets transferred to its virtual counterpart. In that sense, the concept of 'real-time' might quite largely overlap, if not match, with that of 'right-time'. As a result, we shall advocate an explicit flexibility in the classification of temporal resolution and set the criteria for measuring the temporal resolution of DTs to be: Unit of Time [UoT].

D6: Lifecycle Stage

Indeed, the output of a DT use case can inform more than a one lifecycle phase of the same asset, and perhaps, as Al-Sehrawy and Kumar (2021) recommend, a vertically integrated DT can dissolve the asset lifecycle phases in a circular manner. Nonetheless, one can argue that vast majority of DT use cases can be seen as primarily targeting a specific lifecycle phase in mind even if other phases find the same generated output beneficial.

Drawing on the different lifecycle phases (i.e.: Initiation; Design; Construction & Assessment; Operation & Maintenance; Redevelopment & Rehabilitation; Decommission) (ISO, 2018), it is extremely important here to point out the difference between these phases as defined in ISO (2018), tracing the development 'of' sustainable cities and smart communities as a whole, compared to how we proffer them here as phases of the smart infrastructure assets lifecycle 'within' smart communities. Without an already existing smart community, like in the former case, DTs would not exist in the first place, let alone operate. However, managing and developing infrastructure assets within an operating and evolving smart community, as in the latter case, is obviously of more relevance to this paper, concerned with using DTs rather than constructing their constituent physical elements and components from scratch.

Initiation: DTs in this phase are mostly used to facilitate the identification and crystallization of emerging smart community development needs through citizens' engagement and participation to build consensus about what their city lacks and subsequently envisaging a desired future state. Several studies involve DT collaborative initiatives like geo-participation and geo-discussion online platforms capturing the city's status quo and fostering public insightful contributions (Haklay et al., 2019; Hasegawa et al., 2019; Nochta el al., 2019). Afzalan and Sanchez (2017) utilized an interactive GIS website interface to allow for interested citizens to suggest their views for bike-share infrastructure planning. (Dembski, Yamu & Wössner, 2019) engaged diverse groups of citizens to engage in evaluating several traffic development digital scenarios represented using VR technology; thus, pave the way for their intrinsic needs to emerge throughout the process. Kovacs-Györi et al. (2020) used social media data and spatial information to understand citizens' feelings and activities across different locations in the city and have a better grasp of ongoing urban dynamics in order to infer the public needs and preferences.

Design: At this stage, DTs can help increase the confidence in infrastructure development plans and designs proposed to achieve the public needs, by revealing how new interventions in the urban environment might unfold. White el al. (2021) suggested using sunlight, wind and seismic sensed data to evaluate the consequences of new buildings on the city features, as well as the impact of known city challenges and risks on them. DTs can be used to ensure urban planning decisions have no negative impact on citizens and wider ecosystem (ODI, 2020); to compare between alternative design options, for example to select the optimal allocations of land use in terms of gross value added and home and job creation (Oléron-Evansa & Salhaba, 2020); or to assess whether new infrastructure developments may hinder current operations (McHugh & Thakuriah, 2018). In a slightly different approach, Barmpounakis and Geroliminis (2020) used DT to deeply investigate the congestion and critical traffic phenomena, generation knowledge that can significantly support the design of new roads.

Construction: relatively fewer studies have investigated the DT use cases during the construction phase. However, an obvious application that promises huge benefits is the underground asset register (Brammall & Kessler, 2020) with a potential to deliver strike-less and safe working environment. Another valuable use case pertains to the monitoring and control of construction progress. Tang et al. (2019) implemented clustering method to assess the progress of urban development works by evaluating the conformance between the planned urban clusters and the captured actual current state.

Operation and maintenance: Myriads of DT case studies were advanced to endow asset managers with better grasp of operating urban assets' behavior and state, thus supporting the delivery of well-run operations and maintain satisfactory quality of services. This includes, but is not limited to, the initiative of Wang et al. (2020) to predict short-term rail passengers flow to support operations' decision making or the monitoring of energy consumption within buildings in real-time to aid operational fault-detection (Francisco et al., 2020).

Redevelopment and rehabilitation: In this phase, insights from DTs are used to reflect on the current state of the urban environment and how, based on the knowledge gained from observing the DT output, this environment and its constituent assets can be further redeveloped and rehabilitated to offer higher level of services and cope with the urban dynamics and changing behavior of social systems. For example, Kourtit and Nijkamp (2018) relied on DT city-scale urban indicators and KPIs to guide setting city redevelopment strategies. Moreover, the continuous monitoring of the heat stress that pedestrians' experiences informed decision makers of redevelopments, including building shades, among other facilities, to overcome this issue (Mavrokapnidis et al., 2021). Another DT approach can be used to direct future redevelopments of road network in such a manner that brings about less air pollution (Honarvar & Sami, 2019). Again, it is worth re-emphasizing here how the integration of asset lifecycle phases can help the exploitation of knowledge gained through one phase, say operation and maintenance, by other following phases, such as redevelopment and rehabilitation (Al-Sehrawy & Kumar, 2021).

Decommission: With the least attention paid by DT researchers and practitioners to this phase, DT continues to promise potential value to be unlocked via real-life applications and case studies. Al-Sehrawy and Kumar (2021) offered a glimpse of how DTs can support the knowledge transfer from old to new assets, direct the end-of-life procedures, whether disposal or decommissioning, towards a circular, rather than linear, asset life-cycle and offer more sustainable solutions.

D7: DT actors & asset stakeholders

While most of the DT use cases identified in the literature do not reflect on this dimension, considering the greater attention they pay to other DT technical aspects and elaborating on the final delivered value, it is expected that any DT use case will have to involve a group of stakeholders. ISO (2018) provides a list of all possible parties that might be interested in the development of smart communities (i.e.: Developer; Infrastructure Owner; Operator; Service Provider; Consultant; Community Authority; Regulator; Investor; Lender; People).

While this list is obviously brough about from an infrastructure asset's point of view, it is useful though to view the acting groups from the DT perspective. Several papers proposed different smart city frameworks and DT development theoretical constructs (see, for example: Kent et al., 2019; Bibri & Krogstie, 2018; Mamta & Nagpal, 2018) from which it was possible to deduce some of the key roles, responsibilities and consequently actors in the process of delivering a DT; these may include the following five key DT actors: "DT Owner", simply the client defining the purpose of the DT and pursued outcomes; "Data Author": the creator and issuer of data; "Data Host": offering repositories to store big data, such as cloud storage service provider; "DT Developer": the consultant responsible for building the DT with technical expertise in the field of information systems, to design the DT system architecture, specifications and built-in functions; and "Data Scientist": responsible for data cleaning, standardising, re-formatting, analyzing, visualizing…etc. in alignment with the DT owner requirements. A DT use case, in the realm of urban planning and city infrastructure management will indeed include both infrastructure asset stakeholders in addition to DT actors; none of which should be overlooked, and in many cases they may actually overlap. Future officials and city leaders are expected to further enrich their knowledge in data science (Kontokosta, 2017), thus an infrastructure asset operator can be the DT owner of an operation and maintenance DT, while having expert personnel responsible for carrying out the duties normally undertaken by a Data Scientist.

CONCLUSION

In this paper, a multi-dimensional DT use case calssification framework is proposed as a standard means to bringing about order and consistency to the increasing ad-hoc attempts of enumerating and grouping DT use cases in the realms of built environment, urban planning and city infrastructure management. As wider adoption of DT takes place, DT use cases will proliferate and more DT approaches will be suggested and improvised. Non-standardised categorization of these use cases may lead to counter results, reflecting a lack of clarity and vision about the real essence of a DT, rather than a manifestation of DT's value and far-reaching potential.

On the other hand, the framework also provides a resource that DT researchers, developers and practitioners can use to refine and clarify their proposed use-cases at the outset of a project, ensuring that each dimension is fully considered, which can consequently facilitate uniform DT procurement.

Future work may involve a literature review of DT use cases classified in accordance with the proposed framework. This would help identify gaps in knowledge and ongoing practices creating a useful guiding resource for DT researchers. At another level, the framework can be considerably supplemented by a standard methodology to help articulate how a classified use case is actually realized in real-world applications; in other words, to endow the framework with standard means to address the question of "'how' a use case is executed?" once the question of "'what' the use case is about?" has been adequately addressed. The recent study by Al-Sehrawy et al. (2021) offers a likely-looking foundation towards addressing this question of 'how' in a standard and consistent way.

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