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A CATEGORICAL APPROACH FOR DEFINING DIGITAL TWINS IN THE AECO INDUSTRY

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SUMMARY: *Operations and Maintenance (O&M) costs account for 60-80% of a facility's lifecycle costs. Using Digital Twins (DTs) can aid in making O&M more effective and efficient, leading to time and cost savings. The concept of DT started in the Aerospace domain, and other industries eventually adopted it. DTs are a new concept to the Architecture, Engineering, Construction, and Operations (AECO) Industry, and there is a lot of confusion around this concept. The purpose of this paper is to provide a DT definition along with a classification structure to create a common ground for understanding DTs in the AECO industry, which leads to easier adoption of DTs. A systematic literature review was completed to identify the existing DT definitions and classification approaches. Then, through a content analysis, the core components of definitions were extracted. The identified components were used to develop a comprehensive and inclusive DT definition for the AECO industry, using the domain language. In a similar fashion, existing DT classification structures were studied, and their components were identified through content analysis. Using the identified components, a DT classification structure was proposed for the AECO industry using domain concepts and terms. The results were validated and refined through a series of semi-structured expert interviews and surveys. Interviewees and survey participants comprised DT experts from academia and industry with diverse backgrounds. The components of the proposed DT definition include virtual representation, data connection between physical and digital entities, analysis, actuation, and frequency of updates. The classification structure consisted of three DT categories, namely Digital Twin Prototype (DTP), Digital Shadow (DS), and Cyber-Physical System (CPS).*

KEYWORDS: *Digital Twins, Digital Shadows, Cyber-Physical Systems, AECO, Classification System, Common Data Environment, Information Management.*

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1. INTRODUCTION

Research shows that Operations and Maintenance (O&M) costs for a building are typically greater than three times the initial construction costs (Fuller, 2016). Leveraging Digital Twins (DTs) can aid in the effective and efficient operations of facilities. Moreover, it can help reduce O&M costs significantly and ultimately lead to more sustainable built environments (Corrado et al, 2022).

1.1 Current State of Digital Twins in the AECO Industry

There has been a growing interest in DTs in the Architecture, Engineering, Construction, and Operations (AECO) domain on the industry and academic side. On the academic side, research trends show a growing number of DT peer-reviewed publications (Emmert-Streib et al, 2023; Ghorbani and Dubler, 2021). In addition, there have been various national and international initiatives to streamline DT implementation in the AECO industry in the past five years. To start with, the Center for Digital Built Britain created a National Digital Twin program to create the foundation for a country-scale DT (Walters, 2019). The Digital Twin Consortium (DTC) was launched in 2020 with members from companies that want to drive DT adoption in multiple industries, including Manufacturing, AECO, Aerospace, Healthcare, and Transportation domains (DTC, 2020). In 2023, the National Institute of Building Sciences (NIBS) created the Digital Twin Integration Subcommittee (DTI-S) to establish the relationship between DTs and building information management (BIM) (NIBS DTI-S, 2023). Moreover, several DT platforms have been developed to aid in implementing DTs, including Microsoft Azure, Autodesk Tandem, Bentley iTwin, and Siemens Building X. These platforms provide the software infrastructure needed to develop DTs. Despite these efforts, there is still confusion around DTs, and people have different concepts in mind when discussing DTs.

1.2 Digital Twins Definitions

A number of papers have gathered and documented the existing DT definitions (Negri et al, 2017; Onaji et al, 2022; Opoku et al, 2021). Other studies have reviewed and analyzed the existing DT definitions. Boje et al. (2020) analyzed twenty-one DT definitions from various industries, including Manufacturing, Aerospace Engineering, and AECO. They concluded that DTs have three main parts (the physical, the virtual, and the data) and identified DT abilities within each part. The physical part has the ability to sense, monitor, and actuate. The data part has the ability to link data and store knowledge, and the virtual part has the ability to simulate, predict, optimize, and delegate tasks to AI agents. In addition, they developed a three-tier generation evolution for the construction of DTs: Generation 1 included monitoring platforms, Generation 2 included intelligent semantic platforms, and Generation 3 included agent-driven socio-technical platforms. VanDerHorn and Mahadevan (2021) reviewed the existing DT definitions and analyzed their characteristics. These characteristics include a physical reality, a virtual representation, and the interconnections between the two. They proposed the concept of "digital twin qualifiers" that distinguish a DT from a digital model. The qualifiers include a virtual representation representing a single instance of a physical system and data from the physical system used to update the virtual representation. Data update frequency falls within the second category of qualifiers and refers to "*the rate at which data is exchanged between the physical system and the virtual representation*."

In another study, Semeraro et al. (2021) analyzed thirty DT definitions and, through content analysis, identified the core concepts in those definitions. They then introduced a DT definition in Manufacturing that includes those concepts: "*a set of adaptive models that emulate the behavior of a physical system in a virtual system getting real-time data to update itself along its lifecycle. The digital twin replicates the physical system to predict failures and opportunities for changing, to prescribe real-time actions for optimizing and mitigating unexpected events observing and evaluating the operating profile system*." Al-Sehrawy and Kumar (2021) reviewed eighteen DT definitions from Manufacturing, Aerospace Engineering, and AECO Industries and analyzed their aim, function, and main components. They concluded that key features of DTs were data communication, vertical integration (i.e., combining all lifecycle phases of a system), horizontal integration (i.e., the connection between different entities – cyber or physical), and fidelity (including visual fidelity, reflectivity fidelity, and performance fidelity).

Similarly, Liu et al. (2021) reviewed twenty-one DT definitions from academic publications and extracted key points from each definition. They concluded that a DT should be individualized (i.e., there is only one digital twin for each physical twin), high-fidelity (i.e., DT can simulate the behavior of the physical twin with high levels of accuracy), real-time (i.e., DT should be updated regularly), and controllable (i.e., changes in one twin (digital or physical)) results in changes in the other twin (physical or digital). Shahzad et al. (2022) reviewed ten DT definitions. They identified several DT characteristics, including 3D visualization, real-time virtual model, live model updates, data standardization, increased collaboration, time management, budget management, live monitoring of assets, improved building sustainability, and enhanced site logistics. However, their definition of characteristics is not clear. Their list of characteristics includes a combination of features (e.g., virtual model), capabilities (e.g., data visualization), requirements (e.g., necessary use of a Common Data Environment (CDE)), benefits (e.g., increased collaboration), and use cases (e.g., asset monitoring). While these studies provide insights into DT components and characteristics, they do not provide classification systems for categorizing the variety of DTs within the AECO industry.

1.3 Digital Twins Classification Structures in Other Industries

Several studies in the Manufacturing domain discuss different types of DTs. Grieves and Vickers (2017) introduced different manifestations of Digital Twins, including Digital Twin (DT), Digital Twin Prototype (DTP), Digital Twin Instance (DTI), and Digital Twin Environment (DTE). According to them, a DT is "*a set of virtual information constructs that fully describes a potential or actual physical manufactured product from the micro atomic level to the macro geometrical level."* A DTP "*describes the prototypical physical artifact and contains the information necessary to describe and produce a physical version that duplicates or twins the virtual version*." DTI "*describes a specific corresponding physical product that an individual DT remains linked to throughout the life of that physical product*." Lastly, a DTE "*is an integrated multi-domain physics application space for operating on DTs for a variety of purposes*." Enders and Hoßbach (2019) proposed a DT classification scheme with six dimensions, including the industrial sector (options: Manufacturing, Aerospace, Energy, Automotive, Marine, Petroleum, Agricultural, Healthcare, Public Sector, Mining), purpose (options: simulation, monitoring, control), physical reference object (options: manufacturing asset, product, human, infrastructure), completeness (options: 1-3 features, more than 4 features), creation time (options: before physical twin creation, after physical twin creation), and connection (options: no connection, one-directional, bi-directional).

Kritzinger et al. (2018) conducted a categorical literature review of Digital Twin publications in the Manufacturing domain. They introduced DT classification systems based on the level of integration, area of focus, and technologies. The level-of-integration categories included digital model ("*a digital representation of an existing or planned physical object that does not use any form of automated data exchange between the physical object and the digital object*"), digital shadow ("*if there further exists an automated one-way data flow between the state of an existing physical object and a digital object, one might refer to such a combination a digital shadow,"* and digital twin ("*if further, the data flows between an existing physical object and a digital object are fully integrated in both directions, one might refer to it as Digital Twin*"). The area of focus categories included production planning and control, maintenance, and layout planning, and key enabling technologies included simulation methods, communication protocols, and other core technologies. Similarly, Singh et al. (2021) classified DTs based on the creation time, level of integration, hierarchical perspective, level of maturity, and sophistication level. *Creation time* categories included Digital Twin Prototype (DTP) (which contains a set of information to create a physical entity) and Digital Twin Instance (DTI) (which is connected to a physical counterpart). *Level of integration* categories included digital models, digital shadows, and digital twins. The *hierarchical perspective* included three levels: System of System (SoS) level, System level, and Unit level. *Level of maturity* classes included: (1) partial DT (contains a small number of data points such as pressure, temperature, and humidity), (2) clone DT (contains all significant and relevant data from the product/system that can be used to make a prototype), and (3) Augmented DT (uses data from the asset along with its historical data and leverages useful data using algorithms and analytics). Finally, sophistication level categories were: (1) Pre-Digital Twin (DT is created before the physical asset is created), (2) Digital Twin (incorporated data from the physical asset related to its performance, health, and maintenance), (3) Adaptive Digital Twin (provides an adaptive user interface and has the capability to learn from preferences of human operators), and (4) Intelligent Digital Twin (in addition to all the above-mentioned features, it has unsupervised machine learning capabilities).

1.4 Digital Twins Classification Structures in the AECO Industry

In the AECO domain, Arup (2019) classified DTs based on their level of sophistication and defined five levels of DTs: (Level 1): "*A digital model linked to the real-world system but lacking intelligence, learning, or autonomy; limited functionality.*" (Level 2): "*A digital model with some capacity for feedback and control, often limited to the modelling of small-scale systems.*" (Level 3): "*A digital model able to provide predictive maintenance, analytics,* *and insights*." (Level 4): "*A digital model with the capacity to learn efficiently from various sources of data, including the surrounding environment*." (Level 5): "*A digital model with a wider range of capacities and responsibilities, ultimately approaching the ability to autonomously reason and to act on behalf of users*.*"* Seaton et al. (2022) took the classification by Arup and named the categories: (Level 1): Descriptive DTs (*for collecting and visualizing data*); (Level 2): Informative DTs (*converting data into information for generating insights*); (Level 3): Predictive DTs (*using real-time data to predict future state*); (Level 4): Comprehensive DTs (*combining level 1,2, and 3 to propose interventions for avoiding problems and achieving better outcomes*); (Level 5): Autonomous and Connected DTs (*using artificial intelligence and machine learning to reduce dependence on human intervention*). This classification system brings a lot of value. However, levels are very reliant on and described through use cases, and each use case can be achieved through different levels. As an example, predictive DTs can have different levels of connection to the physical world. Therefore, the categories are not defined to a level of specificity to be mutually exclusive. For instance, a DT that uses artificial intelligence to make predictions can either be in level 3 or level 5.

1.5 Knowledge Gaps

In the realm of the AECO industry, it has become increasingly evident that the DT concept is disparate and often misunderstood. Siloed DT definitions have proliferated within this sector, leading to confusion and hindrance in the broader adoption of this transformative technology. Unlike other sectors, AECO's unique characteristics, such as diverse stakeholders with varying levels of expertise and different interests, necessitate a tailored approach to understanding DTs. Existing DT classification systems, while effective in the manufacturing industry, fall short in addressing AECO's multifaceted requirements, leaving them largely overlooked. For instance, while a DT in manufacturing may focus on optimizing a specific production process, in AECO, it could range from monitoring a single asset to monitoring an entire multi-building campus operation. In performing research on the breadth of DTs, we did not identify a definition that caters to AECO's unique characteristics. Despite a notable Arup's classification system defining five levels, its complexity inhibits widespread adoption within the industry. Each level is linked to use cases that create the challenge of applying a uniform taxonomy across diverse projects. Without a common domain language and tangible examples, bridging these knowledge gaps remains elusive and limits the widespread implementation of DTs in the AECO industry. Therefore, this paper addresses these critical issues by presenting a comprehensive DT classification structure tailored to the unique needs of the AECO industry. In addition to providing a succinct and inclusive definition of DTs within this context, the primary objective of this research is to demystify the confusion surrounding DTs and promote and facilitate their adoption in the AECO domain.

2. RESEARCH METHODS

The DT definition and classification structure were developed through a focused content analysis of existing literature combined with expert surveys and interviews (see Figure 1).

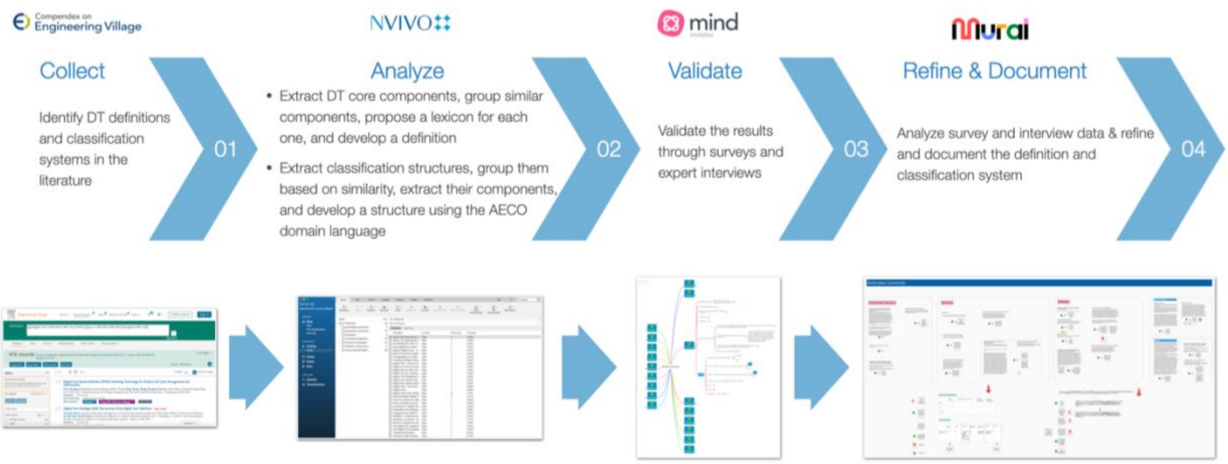

Figure 1: Research Methodology Overview to Develop the DT Definition & Classification Structure.

2.1 Systematic Literature Review

A systematic literature review was completed to identify the definitions and classification structures for DTs. The following keywords were used to search for sources: “Digital Twin definition,” “Digital Twin attributes,” “Digital Twin characteristics,” “Digital Twin Components,” “Digital Twin Classification System,” “Digital Twin Taxonomy,” and “Digital Twin Ontology.” Academic and industry sources from the AECO Industry, as well as other industries (e.g., Manufacturing, Electrical Engineering, Aerospace Engineering, Systems Engineering, Industrial Design, Mechatronics, and Healthcare), were searched. For academic papers, the Compendex database was used to identify the related academic papers. The following criteria were used to select the publications:

1. Only papers written in English were considered for the review.
2. Similar studies by the same authors were removed from the review.
3. Non-peer-reviewed academic papers were removed.
4. Papers published in predatory journals were removed. Beall’s list of potential predatory journals and publishers was leveraged to identify and remove such papers from the review (Beall’s List of Potential Predatory Journals and Publishers, 2023).

Industry sources included the following:

1. Vendor sources such as white papers or websites (e.g., Bentley website, Microsoft white paper, Siemens white paper)
2. Associations and non-profit organizations reports (e.g., Digital Twin Consortium (DTC) reports, Royal Institute of Chartered Surveyors (RICS) report, Aerospace Industries Association (AIA) report)
3. Consulting reports (e.g., Arup Digital Twin report)
4. Magazines (e.g., Engineering News-Record (ENR))

After identifying the sources, the abstracts were studied to ensure that the paper’s content was related to the topic of this research, and the list of papers was refined. Initially, 421 sources were identified. After reading the manuscripts, papers that did not include any original DT definition were removed. After reviewing the manuscripts, 35 sources were included in the analysis (all definitions are included in Appendix A).

2.2 Content Analysis

After reviewing the full manuscripts, content analysis was conducted to extract DT definitions, their core components, and classification structures from the sources. For this research, NVivo V14 software was used for the content analysis. After extracting definitions from the sources, they were analyzed to identify the core components of each definition, and the components were documented with the exact lexicon used in the sources. After an initial round of analysis, similar terms were grouped, and a lexicon was proposed for each component group. For instance, the following terms were grouped together since they refer to similar concepts: “virtual reflection,” “computational model,” “virtual representation,” “digital replica,” “digital copy,” and “computerized model.” In this instance, “virtual representation” was selected as the term used to describe this core component group. A DT definition was developed and documented by using the identified core components. The same procedure was conducted for developing the classification system. The identified categories were grouped based on similarity, and a classification system was derived for the AECO industry using those categories and common domain language.

2.3 Validation: Surveys

The results were validated through surveys and semi-structured expert interviews. This approach enabled us to triangulate our data sources, ensuring the robustness and richness of our study’s qualitative insights. Purposeful and snowball sampling were used to collect participants. An initial list of industry and academic DT experts was prepared through our professional network. The survey link was sent to the experts on the list. The participants were asked to complete the survey, and there was a question at the end to indicate whether they were interested in a follow-up interview. Surveys were collected anonymously. However, if a participant indicated an interest in a follow-up interview, they would voluntarily provide their email address to be contacted for setting up the interview. For snowball sampling, there was a question at the end of the survey to ask if the participant knew any other DT experts that could be contacted for this study. The surveys were administered through Qualtrics.

The survey encompassed three main sections: (1) demographics, (2) DT definition and core components, and (3) DT classification structure. These sections included a mix of question types, incorporating both open-ended questions that encouraged participants to provide additional insights and questions that required participants to gauge their agreement on a Likert scale. The open-ended questions allowed participants to offer nuanced feedback on the research findings. The Likert scale questions were used to evaluate the comprehensiveness, ease of understanding, and accuracy of DT definition and classification structure on a scale of 1 to 10. Furthermore, participants were asked to categorize each DT component as required, optional, or not part of DT. A copy of the survey can be accessed at https://scholarsphere.psu.edu/resources/e3057cf0-c4ba-4195-a560-3228fcea9c6b.

Only data from completed surveys were included in the subsequent data analysis. The survey encompassed a diverse and well-represented set of participants. The responses of only one participant per organization were considered for the analysis to limit the potential bias of any one organization's perspective of DTs, resulting in 22 data points for the analysis.

The survey was directly sent to 40 experts, and 22 completed the survey for a response rate of 55%. 11 additional people responded based upon one expert forwarding the survey link to a group in their organization. Such responses were reviewed but not included since only one response per organization was considered for the analysis. Among those participants, 14 held industry jobs, and 8 worked in academia. Geographically, the majority of the participants were based in the United States, accounting for 18 individuals, while Europe was represented by 2 participants. The remaining 2 participants were located in other regions of the world. In terms of academic participants, they all held the job title of faculty, with years of experience ranging from 5 to 40 years, with an average of 17.6 years. The industry participants were distributed across a range of job categories, including executives, individuals in technology-related roles, project engineers, and architects (see Figure 2 for the distribution of job categories of participants.) Their industry experience varied from 3 to 43 years, with an average of 22.9 years.

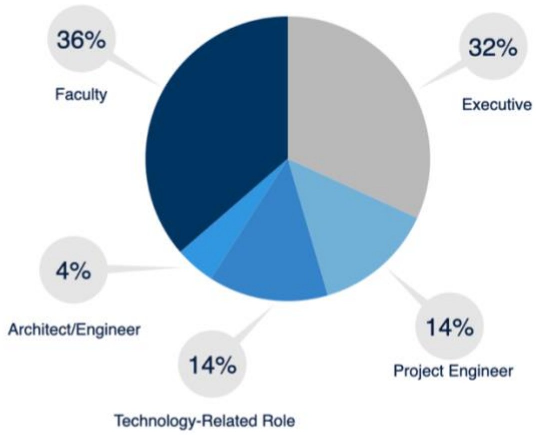

Figure 2: Distribution of Participants' Job Categories.

2.4 Validation: Interviews

Semi-structured interviews were conducted to validate the research results. Interview questions included follow-up questions from participants' survey responses on DT definition and core components and DT classification structure. Since the participants were geographically dispersed, the majority of the interviews were carried out via a video call. The number of interviews was determined by the data saturation principle, ensuring a comprehensive exploration of the study's objectives. A total of 18 interviews were carried out with an approximate length of time of 30 minutes each. Among those interviews, 14 were conducted remotely, and 4 were conducted in person. Interviews were transcribed using an automated tool, Otter.ai. An online mapping tool (MindMeister) was used for the initial note-taking and documentation of the interview results. NVivo 14 was used for coding and analysis of the interview transcripts.

2.5 Survey and Interview Data Analysis

The DT definition and classification structure were refined and documented based on data from validation surveys and expert interviews. Potential suggestions for each change from the interviews were identified and documented using an online mapping tool (Mural). For each question theme, interview and survey comments were grouped based on similarities. Then, the comments were categorized and addressed accordingly:

1. Comments that were based solely on the interviewee's opinion without any supportive information or logic: these comments were documented. However, no change was made to the research results.
2. Comments that were backed up by logic, a set of facts, literature, collective expert opinions, or other type of meaningful information: changes were made to address these comments.
3. Comments that made logical sense but did not fit into the scope of this research: these comments were documented. However, no change was made to the research results.
4. Comments that were not supported by a logical justification; these comments were documented. However, no change was made to the research results.

After addressing the comments, the final revised definition and classification structure were developed and documented.

3. RESULTS AND DISCUSSION

Figure 3 includes the results of the validation survey pertaining to the DT classification structure, components, and definitions. Participants were asked to rate their level of agreement with statements assessing the comprehensiveness, ease of use, and accuracy of each concept using a 10-point Likert scale. The mean and standard deviation (SD) of ratings, along with the box plots, are presented in Figure 3.

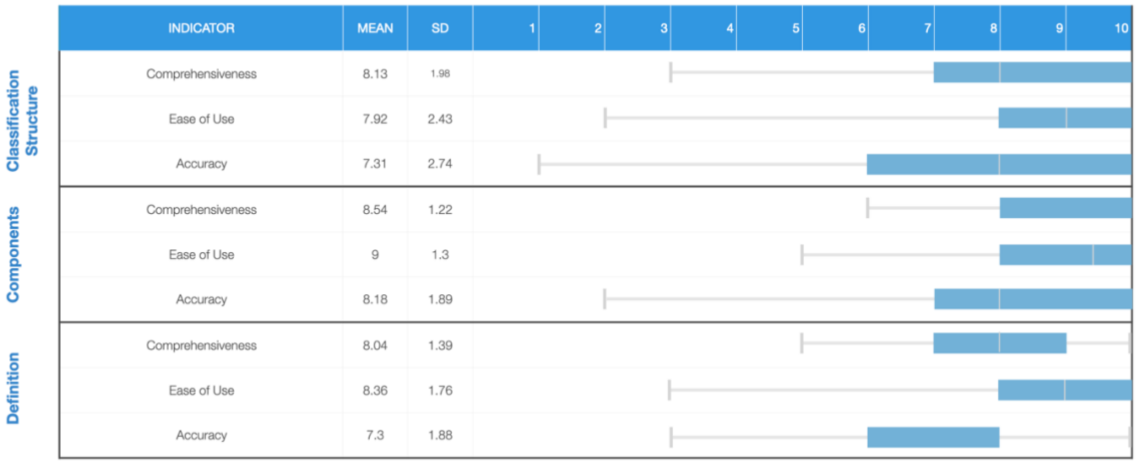

Figure 3: Survey Results.

In the context of classification structure assessment, the medians for the three metrics, namely comprehensiveness, ease of use, and accuracy, are 8, 9, and 8, respectively. These values signify that 50% of the survey participants rated these indicators above 8, 9 and 8, indicating a substantial level of agreement on the comprehensiveness, ease of use, and accuracy of the classification structure. Box plots further emphasize this substantial level of agreement by revealing the interquartile range, where the lower and upper boundaries encapsulate the 1st and 3rd quartiles. In this range, the responses for comprehensiveness, ease of use, and accuracy predominantly fall within the intervals of 7 to 10, 8 to 10, and 6 to 10. Consequently, it is evident that a significant portion of participants expressed positive opinions regarding these aspects of the DT classification structure. For DT components, the medians for comprehensiveness, ease of use, and accuracy are 10, 9.5, and 8. The majority of responses within these categories predominantly fall within the 8 to 10 range for comprehensiveness, 8 to 10 for ease of use, and 7 to 10 for accuracy. In the context of DT definition, the medians for comprehensiveness, ease of use, and accuracy are situated at 8, 9, and 8. Responses for these parameters fall within the ranges of 7 to 9, 8 to 10, and 6 to 8. Overall, the box plots highlight the positive consensus among survey participants, supported by a large majority expressing high levels of agreement, as indicated by the median and quartile values.

The next section delves into the refined research results after the validation process.

3.1 Digital Twin Classification Structure

A structure was developed to classify DTs in the AECO Industry based on their level of integration and the connection between digital and physical twins. The three classes include Digital Twin Prototype (DTP), Digital Shadow (DS), and Cyber-Physical System (CPS) (see Figure 4).

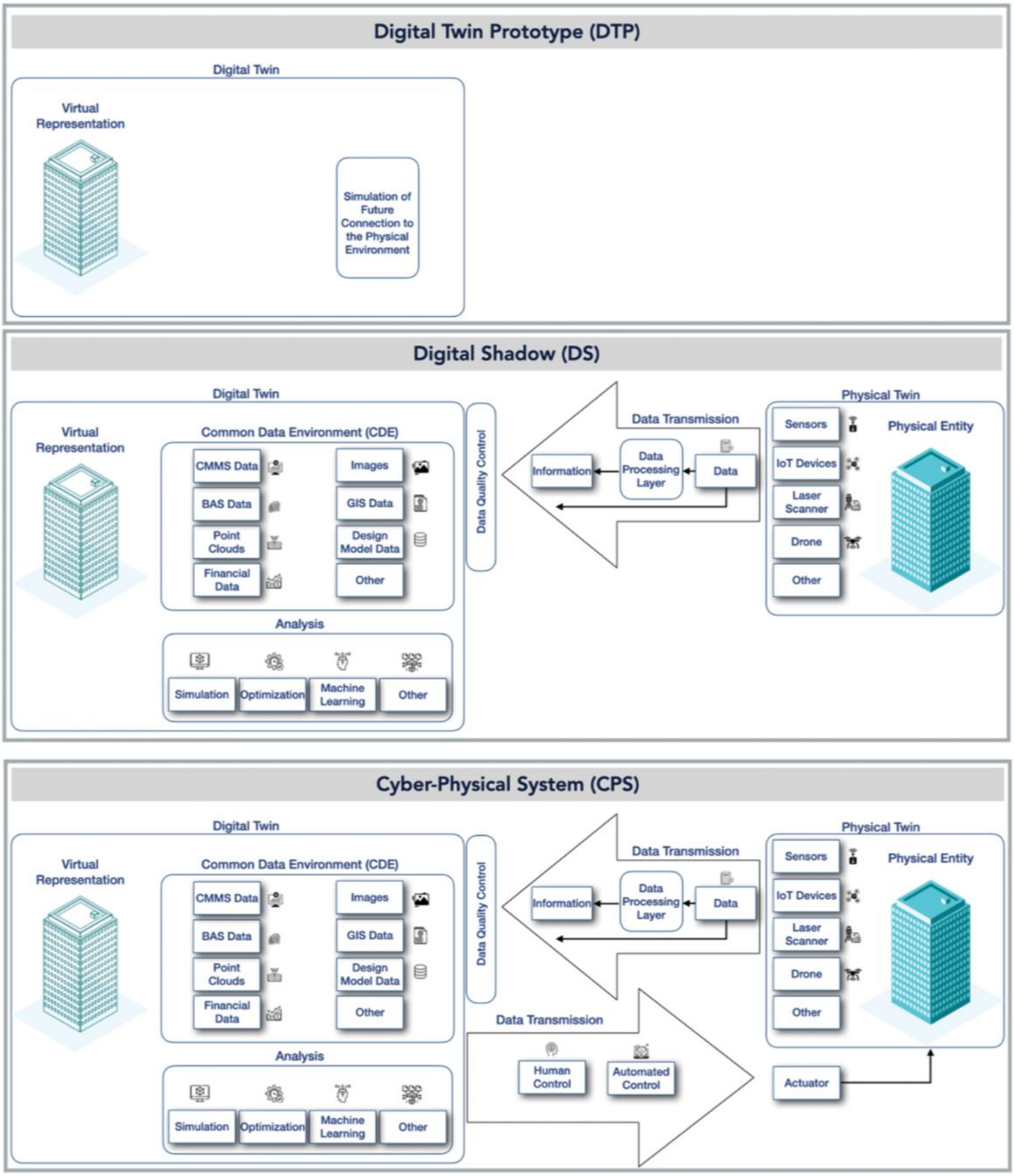

Figure 4: Digital Twin Classification Structure.

The terms for all three classes (DTP, DS, and CPS) have been previously used by researchers to describe different aspects of digital twins. The definitions presented below are aligned to clearly distinguish between the three classes, so the following definitions leverage previous efforts but are unique to this classification structure and the AECO industry.

3.1.1 Digital Twin Prototype (DTP)

A Digital Twin Prototype (DTP) is a virtual representation of an asset designed to be connected to the physical asset in the future.

Within this classification structure, a DTP is not just a digital model. The key distinction is that a DTP includes simulations of future connections to the physical environment. An example use of DTP is to simulate different design scenarios and assess their impact on indoor air quality through virtual sensors.

3.1.2 Digital Shadow (DS)

A Digital Shadow (DS) is a virtual representation of an asset with data flow from the built asset to its digital twin.

An example use of DS use is to capture asset conditions through the use of technologies such as laser scanning or photogrammetry.

3.1.3 Cyber-Physical System (CPS)

A cyber-physical system (CPS) is a virtual representation of an asset with bi-directional data flow between the digital and physical twins, often including an actuation layer.

An example use of CPS is to remotely actuate assets, such as fans, pumps, or electrical equipment.

An asset can have multiple DTs in different categories. For instance, there could be a CPS of a building automation system (BAS), where bidirectional interactions occur between the digital BAS and the physical building system components, e.g., pumps, fans, and sensors. Simultaneously, the scenario may involve a DTP to simulate future situations that do not exist yet. Alternatively, there could be several DTPs in the planning stage for renovation projects for the same assets. There is no inherent hierarchy of maturity among these categories of DTs, and they can coexist and collaborate. Ultimately, selecting the appropriate category for each DT is contingent upon its intended purpose(s) and use case(s).

3.2 Digital Twin Components

The identified DT components in the literature included virtual representation, analysis, data flow from physical to digital, data flow from digital to physical, actuation, and frequency of updates (see Table 1 for the proposed and alternate components along with their frequency). A more detailed discussion of each is provided in this section.

Table 1: Proposed vs Alternate Lexicons for DT Components.

Proposed Lexicon	Frequency (in 35 references)	Alternate Lexicons Used in the Literature
Virtual Representation	35	*Mirror image, digital representation, digital replica, computerized model, near-real-time digital image, virtual model, living model, virtual substitute, a set of virtual information, virtual replica, digital copy, dynamic virtual representation, virtual reflection, comprehensive digital representation, semantic data model, exact and real-time cyber copy*
Analysis	15	*Computational model, designed to optimize, simulated data flow, optimize business performance, it can simulate its physical counterparts' characteristics, behaviour, life, and performance, simulation models, functionality, data processing, simulation,*
Data Flow from Physical to Digital	16	*Physical data, getting real-time data to update the DT, synchronization, DT evolves along with the real system, dynamic status data, working data captured during real-time operation, collecting real-time data from the asset, sensor updates, dynamically updated with data from its physical twin, receive product information*

Data Flow from Digital to Physical	7	*Feedback, data transmitted by sensors, virtual data (and interaction between physical and virtual data), synchronization, knowledge that can be transferred to the real object, receive product information*
Frequency of Updates	8	*It should be updated regularly, synchronized in real-time, collecting real-time data from the asset, continually updated, throughout the lifecycle, real-time updates, synchronized at a specified frequency*
Actuation	3	*Prescribe real-time actions for optimizing and mitigating unexpected events, inform decisions that realize value*

3.2.1 Virtual Representation

Virtual representation, as an integral component of DTs, serves as the medium through which the digital counterpart is created and linked to its physical counterpart. It acts as the entity that corresponds to and mirrors the physical entity in the virtual environment, allowing analysis of the physical system. While 3D geometric models are the most commonly associated form of virtual representation in the context of DTs in AECO, it is essential to acknowledge that virtual representations can manifest in a variety of forms (see Figure 5). 2D representations, for instance, can represent objects or systems where a third dimension is not a crucial factor. Such representations are prevalent for use cases such as space planning, where a simplified 2D visual representation effectively captures and presents the essential information for analysis. A schematic is another example that offers a way to represent complex systems using symbols and interconnected diagrams. These schematics are invaluable where there is a network of components, and they need to be documented and analyzed as a system along with the interaction among them. In such cases, the use of schematics as virtual representations can enhance the understanding of DT.

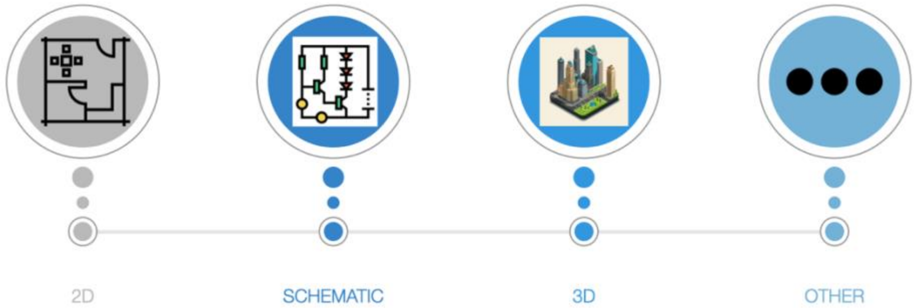

Figure 5: Various Types of Virtual Representation.

3.2.2 Analysis

Analysis plays a pivotal role in enhancing the intelligence of DTs. Among the various forms of analysis discussed in the literature, simulation stands as a prominent one. Simulation-based analysis allows DTs to replicate the real-world behavior of physical entities and predict their responses under different conditions. There are other analytical tools for DTs that encompass machine learning (ML) and deep learning (DL) models. These models not only mimic real-world systems but also continuously learn, adapt, and make data-driven predictions. By integrating ML and DL models in DTs, DTs gain the capacity to recognize patterns, anomalies, and trends in the data, thereby facilitating more informed decision-making.

3.2.3 Data Flow from Physical to Digital

Integrating physical and digital twins is an essential aspect of DTs that facilitates the exchange of information and synchronization between the physical and virtual environment. This connectivity is achieved through the transition of data from the physical twin to the digital twin. In DTs, this data flow takes place within both Digital Shadows and Cyber-Physical System categories. The data itself is collected from the physical environment using a diverse array of sources such as sensors, IoT devices, laser scanners, drones, and other data collection devices. The data is then transmitted to the DT, where it can be incorporated into its raw, unprocessed form or undergo processing, cleaning, and structuring to transform it into actionable information. The transition process may be automated, semi-automated, or manual, depending on the specific DT use case and the level of precision required. Regardless of the data's nature or the transfer process, a crucial step in the data exchange is the implementation of a data governance process (Alreshidi et al, 2014). This process ensures that the data is not only valid but also meets the necessary quality standards, which is paramount for achieving accurate and reliable insights within the DT system. This interplay between the physical and digital twins through controlled data flow is fundamental to the effectiveness and functionality of DTs.

3.2.4 Data Flow from Digital to Physical

The exchange of data from the digital environment to the physical environment represents a fundamental characteristic of DTs and is a feature exclusive to DTs operating at the CPS level. This transmission plays a pivotal role in enhancing the real-time responsiveness of the physical twin by infusing it with data-driven insights. The transmitted data from the DT can serve as a valuable informant, influencing the decision-making process in two potential ways: Firstly, it can inform human operators, providing them with critical information to make informed decisions and take action accordingly. Secondly, it can inform automated controllers, which can execute pre-defined actions or algorithms in response to the data received, enabling autonomous adjustments in the physical environment. This dynamic data flow from the digital to physical environments, guided by principles of data-driven decision-making, highlights the transformative potential of DTs in realizing the vision of intelligent and adaptive systems.

3.2.5 Frequency of Updates

The time dimension of DTs, as governed by the update frequency, constitutes a critical component that directly impacts their relevance in various use cases. The update frequency signifies how often the DT data gets updated and is closely tailored to the specific use case at hand. The choice of update frequency is inherently tied to the nature of the use case and the associated urgency of response. For instance, in high-stakes scenarios like a hospital's operation room, where indoor air quality can be a matter of life and death, real-time updates are indispensable, often occurring at minute intervals to enable rapid interventions. In contrast, when assessing indoor air quality in a residential apartment, the urgency may be lower, and hourly updates can provide sufficiently informative and efficient data. This critical aspect of DT, reflecting the dynamic interplay between use case demands and data acquisition, underscores the adaptability and versatility of DTs across a spectrum of applications, ensuring that their temporal dimensions align seamlessly with the specific needs of each scenario.

3.2.6 Actuation

Actuation embodies the power to make changes in the physical environment. This capability can manifest in two ways, either through automated processes driven by data-driven insights and algorithms or through user-informed actions, where human decision-making plays a role in influencing the physical environment. Actuation is a component exclusively present in DTs operating at the CPS level. In this context, a DT serves as a dynamic and responsive entity that not only observes and mirrors the physical world but also actively participates in it, taking actions that can range from optimizing energy consumption in a building to controlling the humidity of a room. This critical aspect of DTs which is unique to DTs operating at the CPS level highlights their potential in enabling intelligent, real-time control and decision-making. It should be noted that the actuation component is closely tied to the other component and dependent on it, "data flow from digital to physical." In other words, actuation would not be possible without data flow from digital to physical twin.

3.3 Digital Twin Definition

Leveraging the identified DT components, a comprehensive and adaptable DT definition was developed as follows:

"*A digital twin of an asset is a fit-for-purpose and intelligent virtual representation of it synchronized at specific frequencies, with an existing or planned connection between the virtual and physical twin that may include analysis and the ability to actuate physical changes from the virtual twin*."

The definition encapsulates the core components of DTs, allowing it to be adaptable and inclusive, catering to all the defined categories (i.e., DTP, DS, and CPS). By highlighting the importance of synchronization, the potential of data-driven analysis, and the capacity of actuation, this definition, along with the classification structure, provides a framework that accommodates the diverse array of DT use cases in the AECO Industry.

3.4 Cyber-Physical-Human System

Amidst the complex web of interconnected components within DTs, the role of human interaction emerges as a pivotal aspect that is often overlooked. Understanding the relationship between humans and the components of the DT system is critical and can shape the efficiency, efficacy, and usability of such systems. In this section, we delve into the critical interplay between different components of DT systems and emphasize the role of humans within these DT systems. Through the exploration of various modes and mechanisms of human interaction with DT systems, we explore ways to enhance their functionality and accessibility. In DT systems, the interaction between humans and DT systems can take place at various junctures (see Figure 6).

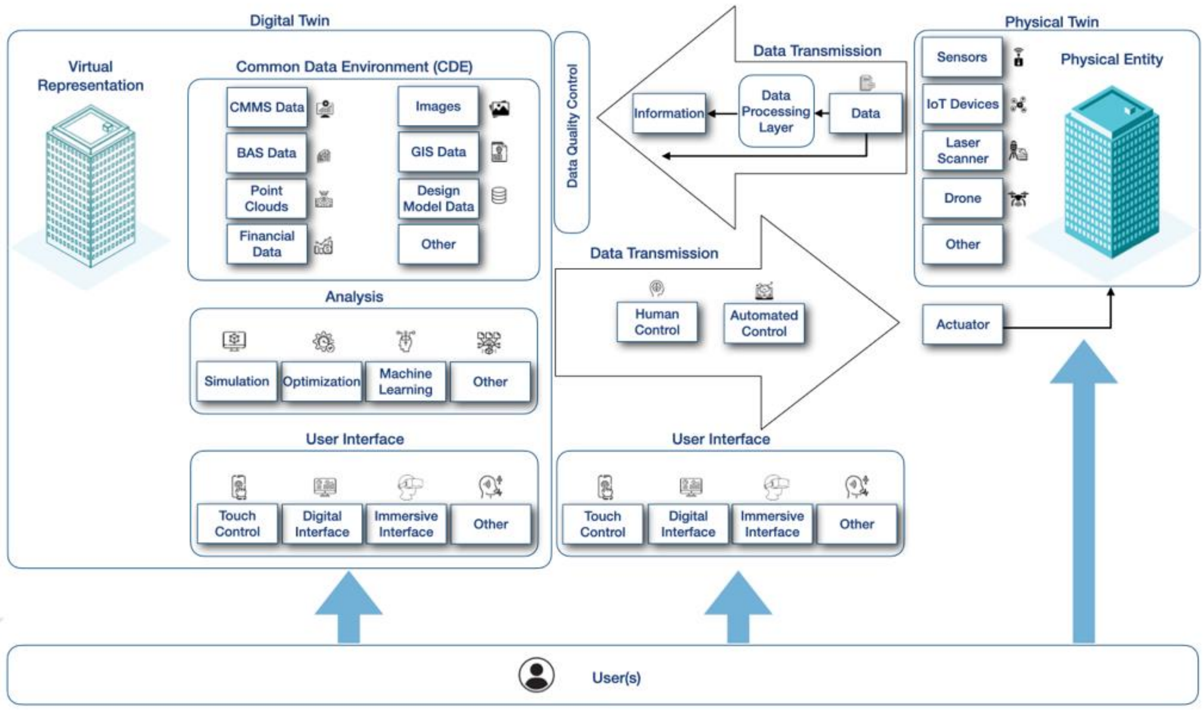

Figure 6: Cyber-Physical-Human System.

There are various means that serve as conduits to interact with DT systems, each offering unique opportunities and challenges. One avenue of interaction lies in interfaces, where users can interact with various components of a DT system through user interfaces. These interfaces facilitate communication between users and the diverse components of the DT system, including the virtual representation, common data environment (CDE), and analytical tools. Within this framework, user interfaces can range from touch control interfaces leveraging touch technology, such as mobile applications, to immersive interfaces experienced through technologies like Augmented Reality (AR) and Mixed Reality (MR), where users engage with DTs through head-mounted displays. Additionally, digital interfaces provide alternative pathways, accommodating interactions via desktop computers or similar devices. Lastly, direct control offers a more tactile dimension to interaction, enabling users to manipulate physical entities within the DT ecosystem directly. For instance, a mechanical technician might respond to a system fault notification by physically shutting down equipment. Understanding and leveraging these diverse modes of interaction are essential steps toward advancing the implementation and efficacy of DT systems.

3.5 Different Types of Relationships Between Digital and Physical Twins

The integration of DT technology with physical entities has revolutionized the way we perceive and interact with real-world systems. The relationship between digital twins and their physical twins extends beyond simple one-to-one connections, encompassing a spectrum of arrangements, from one-to-many to many-to-many (see Figure 7). Understanding and leveraging these diverse relationships is essential for unlocking the full potential of DTs.

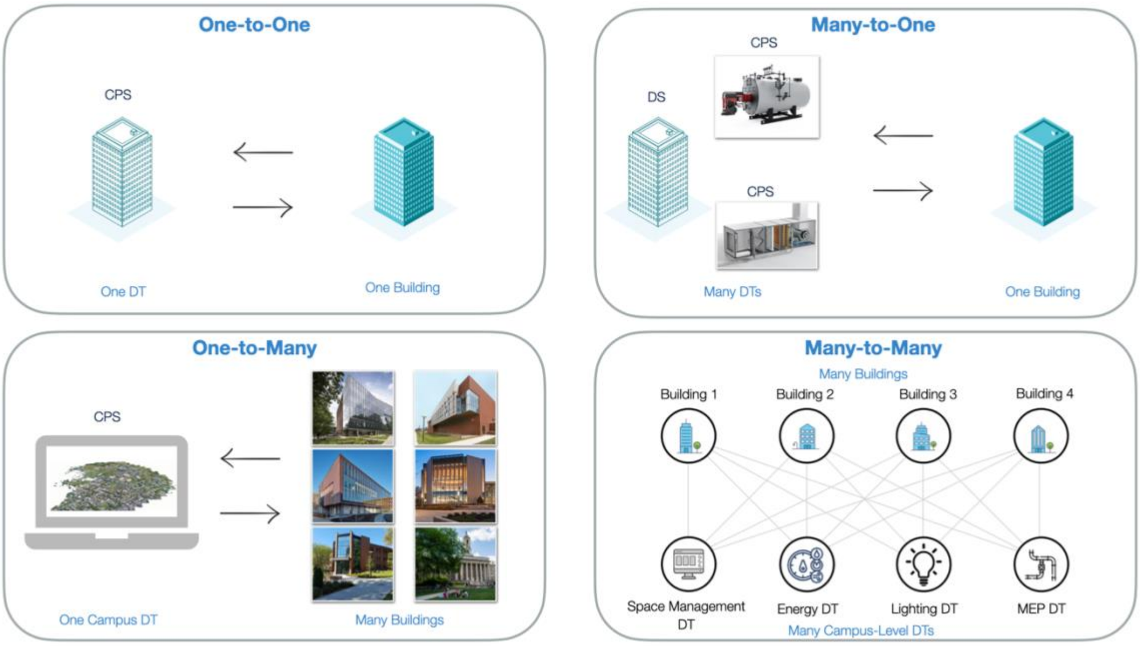

Figure 7: Various Types of Relationships between Digital and Physical Twins.

3.5.1 One-to-one relationship

In a one-to-one relationship, a single digital twin corresponds directly to one physical twin. A prominent illustration of this configuration is the DT of a building.

3.5.2 One-to-many relationship

A one-to-many relationship represents a DT linked to multiple physical twins. For example, within a campus-wide DT at the CPS level, a single DT can be connected to several buildings on campus. This interconnected web allows for centralized management of assets.

3.5.3 Many-to-one relationship

Conversely, a many-to-one relationship involves multiple DTs converging on a single physical twin. Consider, for example, a complex asset, such as a building. In this scenario, various DTs can serve distinct purposes, each focusing on a specific aspect of the asset. One DT (at the DS level) could monitor energy consumption, while another DT (at the CPS level) could monitor and control mechanical equipment like boilers and air handling units. These DTs can interact and communicate with each other.

3.5.4 Many-to-many relationship

The most interconnected relationship is the many-to-many configuration. In such a configuration, numerous DTs are connected to multiple physical twins.

To illustrate this, envision buildings on a campus, each having their individual DTs. If each element of each building is integrated into each system (e.g., Space Management System DT), and each system (e.g., Space Management System) is incorporated into each building, we will have a many-to-many relationship.

4. SUMMARY AND CONCLUSIONS

The concept of Digital Twins (DTs) has gained significant attention within the Architecture, Engineering, Construction, and Operations (AECO) Industry. However, the adoption of DTs in the AECO Industry is still in its early stages, primarily due to the lack of a common language and a clear understanding of the DT concept. This paper addressed this issue by developing a definition for DTs in the AECO industry through a systematic literature review and content analysis: "*A digital twin of an asset is a fit-for-purpose and intelligent virtual representation* *of it synchronized at specific frequencies, with an existing or planned connection between the virtual and physical twin that may include analysis and the ability to actuate physical changes from the virtual twin*."

The definition emphasizes that each DT is created for a specific purpose. In other words, the purpose and use case(s) of a DT should be determined prior to creating it. Furthermore, a classification structure was developed to demonstrate various categories of DTs based on the level of integration and connection between digital and physical twins. The structure comprises three categories of DTs, including Digital Twin Prototype (DTP), Digital Shadow (DS), and Cyber-Physical System (CPS). The proposed DT definition is flexible and accommodates all three categories of DTs. Importantly, the classification structure recognizes that an asset can have multiple DTs from different categories simultaneously, reflecting the diverse nature of DT applications. The developed definition and classification structure were rigorously validated through expert surveys and interviews, providing a foundation to clarify the ambiguity surrounding DTs and encourage DT implementation in the AECO industry.

In conclusion, this research contributes to demystifying the ambiguity surrounding DTs and provides a common language and ground for the AECO Industry. The results facilitate the communication of DT discussions between various project stakeholders. In addition, the findings foster creativity and help users understand the concept of DTs more clearly. The research results pave the way for enhanced integration of DTs into industry practices and set the stage for further exploration, including the development of an ontology for DT use cases. As the AECO Industry continues to embrace digitalization, the DT classification structure and definition presented in this paper will play a pivotal role in shaping the future of the industry.

LIMITATIONS AND FUTURE WORK

The exploration of the DT concept in the AECO industry is still in its early stages. Real-life examples of larger-scale DTs are limited, leading to a reliance on focused system-level DTs or hypothetical scenarios to illustrate certain concepts, such as the dynamics of many-to-many relationships between digital and physical twins. The scarcity of empirical evidence may affect the depth of understanding and applicability of DT principles in practical contexts. Furthermore, the DT elements presented in each DT category may not be comprehensive. As technology continues to evolve, novel elements may emerge that will need to be included in these systems. For instance, the advent of new data collection tools beyond IoT devices, sensors, and laser scanners could necessitate revisions or expansion to the DT elements.

To advance the understanding and implementation of DT within the AECO domain, we propose the following avenues for future research. (1) Development of a DT Use Ontology: establishing a standardized terminology and ontology specific to DT applications can enhance clarity and facilitate effective communication within the industry. by delineating and formalizing various DT uses, stakeholders can better comprehend their potential applications and implications across diverse projects and organizations. (2) Development of a DT Implementation Plan: formulating a DT implementation plan is crucial for guiding organizations through the process of creating and integrating DTs into their operations. The implementation plan would encompass a range of considerations, including selecting DT uses, technological requirements, and data management strategies. By creating clear guidelines and best practices, organizations can streamline the adoption of DTs, thereby maximizing their potential benefits while mitigating challenges. (3) Detailed case studies of existing and future DT initiatives.

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APPENDIX A: DIGITAL TWIN DEFINITIONS TABLE

Industry	Year	Definition	Reference
AECO	2018	*A digital twin is a mirror image of a physical process that is articulated alongside the process in question, usually matching exactly the operation of the physical process which takes place in real-time.*	Batty, 2018
AECO	2018	*A realistic digital representation of assets, processes or systems in the built or natural environment*	Bolton et al., 2018
AECO	2019	*A digital twin is a digital replica of a physical built asset. What a digital twin should contain and how it represents the physical asset are determined by its purpose. It should be updated regularly to represent the current condition of the physical asset. A digital twin should be standardized yet extensible, able to address key use cases directly and specialty use cases with extensions, cloud and computationally friendly, scalable, and verifiable.*	Brilakis et al., 2019
AECO	2019	*A digital twin is the combination of a computational model and a real-world system, designed to monitor, control, and optimize its functionality. Through data and feedback, both simulated and real, a digital twin can develop capacities for autonomy and to learn from and reason about its environment*	Arup, 2019
AECO	2019	*A cyber-physical-social system with coupled properties*	Tomko and Winter, 2019
Manufacturing	2015	*Very realistic models of the current state of the process and their behaviors in interaction with their environment in the real world – typically called the "Digital Twin".*	Rosen et al., 2015
Manufacturing	2017	*A virtual representation of a product on the shop-floor*	Blum and Schuh, 2017
Manufacturing	2017	*A digital twin is a computerized model of a physical device or system that represents all functional features and links with the working elements.*	Chen, 2017
Manufacturing	2017	*A Digital twin is the digital representation of a unique asset (product, machine, service, product service system or another intangible asset), that compromises its properties, condition and behaviour using models, information and data*	Stark et al., 2017
Manufacturing	2017	*(as a software) A digital representation of all the states and functions of a physical asset*	Weber et al., 2017
Manufacturing	2018	*A comprehensive digital representation of an individual product. It includes the properties, conditions, and behavior of the real-life object through models and data*	Haag and Anderl, 2018
Manufacturing	2018	*The Digital twin of a physical object as the sum of all logically related data, i.e. engineering data and operational data, represented by a semantic data model*	Kunath and Winkler, 2018
Manufacturing	2018	*A near-real-time digital image of a physical object or process that helps optimize business performance*	Scaglioni and Ferretti, 2018
Manufacturing	2018	*A virtual, dynamic model in the virtual world that is fully consistent with its corresponding physical entity in the real world and can simulate its physical counterpart's characteristics, behaviour, life, and performance in a timely fashion*	Zhuang et al., 2018

Manufacturing	2019	*The digital twin model is an exact and real-time cyber copy of a physical manufacturing system that truly represents all of its functionalities*	Leng et al., 2019
Manufacturing	2019	*DT is a multi-domain and ultra high fidelity digital model integrating different subjects such as mechanical, electrical, hydraulic, and control subjects. It connects multiple product activities, and is a consistent model supporting design, production, operation, maintenance, and recycling lifecycle stage.*	Luo et al., 2019
Manufacturing	2019	*This rich digital representation of real-world objects/subjects and processes, including data transmitted by sensors, is known as the digital twin model.*	Nikolakis et al., 2019
Manufacturing	2019	*A real mapping of all components in the product life cycle using physical data, virtual data and interaction data between them*	Tao et al., 2019
Manufacturing	2019	*Digital Twin is essentially a unique living model of the physical system with the support*	Wang et al., 2019
Manufacturing	2021	*A set of adaptive models that emulate the behavior of a physical system in a virtual system getting real-time data to update itself along its lifecycle. The digital twin replicates the physical system to predict failures and opportunities for changing, to prescribe real-time actions for optimizing and mitigating unexpected events observing and evaluating the operating profile system.*	Semeraro et al., 2021
Manufacturing	2021	*Fit for purpose digital representation of an observable manufacturing element with synchronization between the element and its digital representation.*	ISO 23247-1, 2021
Metachronics	2016	*Digital Twin is the collection of relevant digital artefacts that involves engineering and operation data, in addition to behavior description using various simulation models. The Digital Twin evolves along with the real system along the whole life cycle and integrates the currently available knowledge about it.*	Boschert and Rosen, 2016
Electrical Engineering	2016	*Digital twins are virtual substitutes of real-world objects consisting of virtual representations and communication capabilities making up smart objects acting as intelligent nodes inside the internet of things and services.*	Schluse and Rossmann, 2016
Electrical Engineering	2018	*Digital twin represents a dynamic digital replica of physical assets, processes, and systems, which comprehensively monitors their whole life cycle.*	He et al., 2018
Electrical Engineering	2018	*A digital twin is a digital model of a real object containing lifecycle records and dynamic status data, which are synchronized in real-time. The model will be used to gain knowledge that can be transferred to the real object*	Eisenträger et al., 2018
Systems Engineering	2017	*Digital Twin is a set of virtual information constructs that fully describes a potential or actual physical manufactured product from the micro atomic level to the macro geometrical level.*	Grieves and Vickers, 2017
Systems Engineering	2018	*a digital twin is a one-to-one virtual replica of a "technical asset" (e.g., machine, component, and part of the environment). A digital twin contains models of its data (geometry, structure, ...), its functionality (data processing, behavior, ...), and its communication interfaces. It integrates all knowledge resulting from modeling activities in engineering (digital model) and from working data*	Schluse et al., 2018

		captured during real-world operation (digital shadow). Simulators are used to make the digital twin experimentable	
Systems Engineering	2020	*DT is defined as a digital copy of a physical asset, collecting real-time data from the asset and deriving information not being measured directly in the hardware.*	Fotland et al., 2020
Systems Engineering	2023	*A digital twin is a dynamic virtual representation of a physical system that continually updated using data from the real-world operational System*	DoD, 2023
Aerospace Engineering	2012	*A Digital Twin is an integrated multiphysics, multiscale, probabilistic simulation of an as-built vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its corresponding flying twin.*	Glaessgen and Stargel, 2012
Aerospace Engineering	2012	*A Digital twin is an integrated multi-physics, multiscale, probabilistic simulation of an as-built vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its corresponding flying twin*	Shafto et al., 2012
Aerospace Engineering	2020	*A Digital Twin is defined as a set of virtual information that mimics the structure, context and behavior of an individual/unique physical asset, or a group of physical assets, is dynamically updated with data from its physical twin throughout its lifecycle and inform decisions that realize value*	Arthur et al., 2020
Industrial Design	2018	*Digital twin of a real distributed product is a virtual reflection, which can describe the exhaustive physical and functional properties of the product along the whole life cycle and can deliver and receive product information*	Tharma et al., 2018
Healthcare	2022	*Health digital twins are defined as virtual representations ("digital twin") of patients ("physical twin") that are generated from multimodal patient data, population data, and real-time updates on patient and environmental variables.*	Venkatesh et al., 2022
Industry-agnostic	2020	*A digital twin is a virtual representation of real-world entities and processes, synchronized at a specified frequency and fidelity.*	DTC, 2020