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Request for Information on the National Digital Twins R&D Strategic Plan

Genda Chen

ENTERPRISE DIGITAL TWIN IN THE BUILT ENVIRONMENT TO ENABLE MULTIFUNCTIONAL MODELING IN LARGE SCALE

Genda Chen, Department of Civil, Architectural, and Environmental Engineering, the Center for Intelligent Infrastructure, Missouri University of Science and Technology, Rolla, MO 65401, USA.

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SYNOPSIS
Digital twin (DT) has been mostly developed for a single function in the literature, limiting its full potential in applications. This document introduces an enterprise DT empowered with a layered integration of multifunctional models in the built environment. The enterprise DT involves open-sourced and secure modeling capabilities for non-profit organizations and for-profit companies, respectively, so that the national DT framework can benefit all entities. The enterprise DT also defines a new concept of the degree of digital twinning (DODT) to a real world by the number of models enabled by a common DT platform. This multidimensional DT is a modular architecture in three hierarchical tiers: autonomous region, infrastructure asset, and operation system. While the asset and system DTs focus on the lifecycle management of buildings and infrastructure as well as systems to support daily operations, the region DT addresses diverse modeling approaches for a comprehensive management of the built environment. The DODT enables value-driven digital replications of a physical twin at different levels. In addition to building information modeling, the enterprise DT enables spatiotemporal analysis in multiple scales to couple nonstructural with structural building components and connect the built environment to planning constructions.

Keywords: Smart cities; Digital twin; Degree of digital twinning; Remote sensing; Asset lifecycle management; Cyber-physical-social system

1 INTRODUCTION

Building and civil infrastructure assets have been managed using a database since 1970 and with the aid of Building Information Modeling (BIM) since 1992 for value engineering and as-built information. The imperative for embracing digital twinning becomes evident in the aftermath of the 2007 Minneapolis Interstate 35W Bridge Collapse, a catastrophic event that claimed 13 lives and injured 145. This tragic incident underscores the critical need for spatiotemporal analysis and societal impact studies, highlighting deficiencies not only in extracting overlooked design information from BIM but also in the incapacity of BIM alone to assess the adequacy of bridge members. The urgency to adopt digital twin (DT) is amplified as the nation's infrastructure is aging, demanding more frequent condition assessment and maintenance, particularly in the face of accelerating climate changes and increasing natural disasters.

Most, if not all, of prior studies on DT have concentrated on a single function, either computational or informational, within a specific discipline such as civil engineering or architecture. For example, DT has been viewed as a computational platform for finite element model updating in a probabilistic context and as an information platform for BIM updating. While these advancements in their respective research fields are intriguing, the broader impact of these isolated applications of DTs is likely constrained.

This document aims to empower DT with a layered integration of multifunctional models in the built environment, creating a cyber-physical-social (CPS) system encompassing buildings, infrastructure, and the associated community. Depending on the specific value-driven use cases of interest, a DT can be tailored through various facets and phases of a physical twin with the following specific objectives:

1. Develop a rapidly implementable framework of DT modules in hierarchical tiers,
2. Replicate the real-world construction of partially completed buildings with spatiotemporal analysis in multiple scales,
3. Integrate computational and informational models into a CPS system for asset lifecycle management,
4. Evaluate the structural and nonstructural behavior of buildings under multiple hazards to address post-disaster resilience of the affected community, and
5. Demonstrate and quantify the values of a DT through a straightforward indicator that is easy to evaluate.

2 DT FRAMEWORK IN THE BUILT ENVIRONMENT

2.1 DT for Product vs. Asset Lifecycle Management

The DT concept originated from the modeling of product lifecycle management (PLM) that handles a product as it moves through the stages of its life. The lifecycle of a product starts when a product is introduced to consumers into the market and ends when it is removed from the shelves. Due to the availability of commercial products in large quantities and short term at relatively low costs, the integration of multiple products into a new system product can easily be viewed as an intended physical prototype. The DT of the system is used to ensure all component products fit together before investing a new system product line in a physical factory. This is a valuable design attribute of DTs in the era of digital manufacturing in addition to real-time monitoring as envisioned originally.

On the other hand, asset lifecycle management (ALM) for large-scale buildings and infrastructure works differently. A set of strategies (e.g., maintenance, rehabilitation, and replacement) is organized and implemented with the intent of preserving and extending the service life of public infrastructure assets, such as roads, bridges, and railways. Unlike commercial products, infrastructure assets are often unique for both esthetical and functional purposes and require capital investment over a long time. As such, the attractive attribute of DTs for product assembly in manufacturing may have no equivalence in infrastructure asset management. For buildings and infrastructure management, computational mechanics modeling is desirable as their physical and functional conditions affect the decision-making of asset management strategies. In addition, using sensing data alone to assess their conditions is costly due to their large scale or even impossible for hidden deterioration. Model updating with limited sensor data is one of the effective ways to provide the needed condition assessment capability.

The above difference between PLM and ALM determines the way in which DTs are applied effectively in the built environment. To start with, the definition of DTs must be modified from those targeted at applications in manufacturing. In the past decade, 29 definitions of DTs were used in academia, industry, government, and software sources. In the built environment, the term DT has been used mainly in three ways: (1) modifying the original DT definition to reflect a realistic digital representation of assets, processes, or systems; (2) extending BIM to enable real-world data capture and feedback or completely replacing BIM; and (3) formulating a closed-loop digital-physical system for built asset delivery and operation. In general, DT differs from BIM in two distinctive ways: (1) two-way digital threads between DT and its represented physical asset, and (2) focus on operation and maintenance instead of the entire lifecycle of an asset as BIM encompasses with an emphasis on design and construction. The BIM implementation for operation is also different from DT's. While the DT supports the operation of built assets, BIM for facility management focuses compiling information of the delivered built asset to support inventory and space management, general upkeep, and building services maintenance, which does not result in an accurate replica of the condition and performance of the asset. In other words, the BIM is a static representation of a structure that shows how it was designed and built. It does not reflect the temporal changes that take place after its construction. On the other hand, the DT is a dynamic imitation that is continuously updated to reflect the current condition, rate of deterioration, effect of restoration, etc.

2.2 DT Definition in the Context of ALM

This document consolidates the three uses of DT term in the literature to propose a novel definition. In this context, a multidimensional DT is defined as *a synergetic, multifunctional, value-added, realistic digital representation of an intended or actual real-world asset, system, or process - a physical twin in the built environment*. As schematically shown in Figure 1, the DT interacts with the physical twin in a closed loop with two digital threads. In the physical-to-digital thread, sensing data and monitoring information obtained from the physical twin can be used to update the digital representation. In the digital-to-physical thread, intervening strategies developed and optimized through scenario studies on the DT can help understand the outcomes of multi-faceted decision-making before they are implemented on the physical twin. On the digital platform, the collected multimodal data from sensors and tests will be fused and evaluated to detect, locate, and quantify abnormalities as well as to predict the remaining life of the physical twin using advanced deep learning-based data analytics.

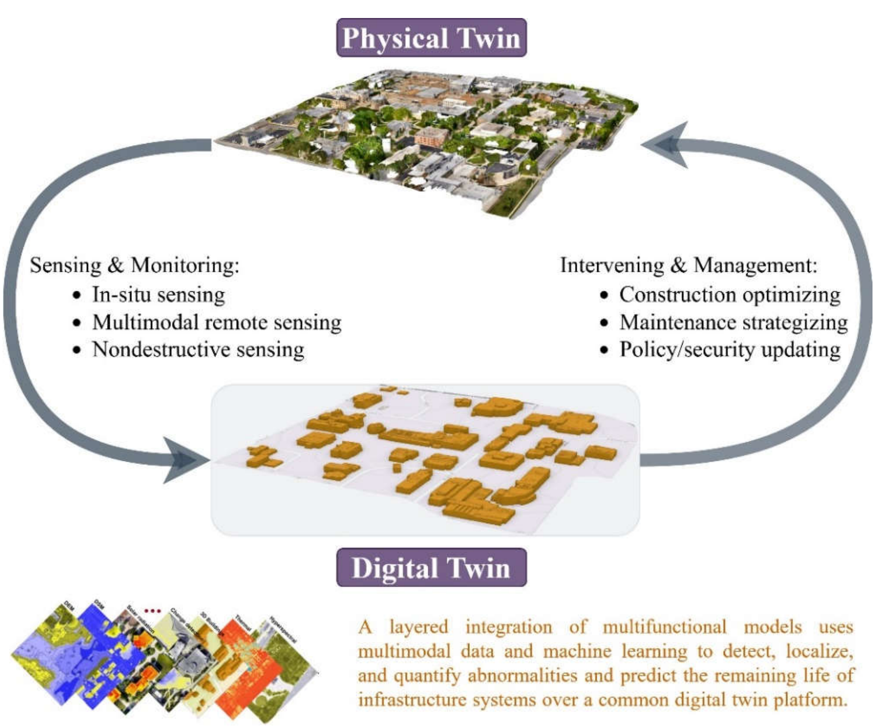

Figure 1 A schematic view of the proposed digital and physical twinning

2.3 Degree of Digital Twinning (DODT)

The state-of-the-art development of the DT technology is primarily focused on digital and physical twinning in computational mechanics or information only. A value-added solution expands the current single function paradigm to multiple functions. To quantify the values of a DT, the cost saving enabled by the DT is the most widely used indicator. However, this indicator requires the collection and use of a wealth of information that is difficult to acquire. In this document, DODT is introduced as a metric to simplify the estimation of the value of a DT by the number of digital models and feature mappings enabled and shared by the common DT platform to address societal needs in multiple disciplines, such as engineering, architecture, security, and social and political sciences. In the context of determining DODT, digital models are defined as a three-dimensional (3D) representation of agents (e.g., person or vehicle) and structures (e.g., buildings and infrastructure), including structural and nonstructural components.

2.4 Connections, Hierarchy, and Architecture of Modulated DTs

The CPS infrastructure concept stands as an innovative and emerging paradigm poised to revolutionize the built environment through the delivery of innovative services. It embodies a comprehensive framework that seamlessly integrates three pivotal components: cyber, physical, and social, as detailed in Table 1. The cyber system provides services to promote economic development and improve the quality of life and human wellbeing. The physical system includes an engineering-to-operation process to ensure safety, functionality, and resilience. The social system describes common traditions, cultures, patterns, and beliefs present in a population group. The main component, key function, and performance evaluation criteria of the three systems are described in Table 1.

Table 1. Characteristics of the three components in the built environment

System	**Main Component**	**Key Function**	**Performance Evaluation Criteria**
Cyber	Internet of Things	Enable people and objects to exchange data via wireless communication and store data in the cloud	Integration tool, security management, endpoint management
	Software	Provide computational modeling and intelligence	User interaction and support services
	Virtual reality	Create the virtual representation of the real world integrated with high-fidelity models	Latency, cybersickness, sense of presence, and technological advances
Physical	Load bearing components	Support service and extreme loads to provide living/working spaces or functions	Vulnerability, design consistency and optimization of elements
	Non-load bearing components	Provide utility facilities and communication infrastructure including computers	Function and security of workspace, economic considerations
Social	Economics	Estimate cost-benefit ratio of major projects	Maintenance costs, strategy development, and profitability
	Social work	Alleviate conditions of people in need of help or welfare	Social and emotional needs, an environment of respect and rapport

DT in the bult environment can be hierarchically structured in a simplified form as shown in Figure 2, extending from the regional level down to asset and system levels. Depending on the security demand, the infrastructure at the asset level can be clustered into two segments: (1) an open-sourced segment catering to public buildings and standard infrastructure, and (2) a secured segment designed for information-sensitive buildings and critical infrastructure. Furthermore, the hierarchal asset and system structure undergoes evolution throughout the planning, design, construction, and operational phases.

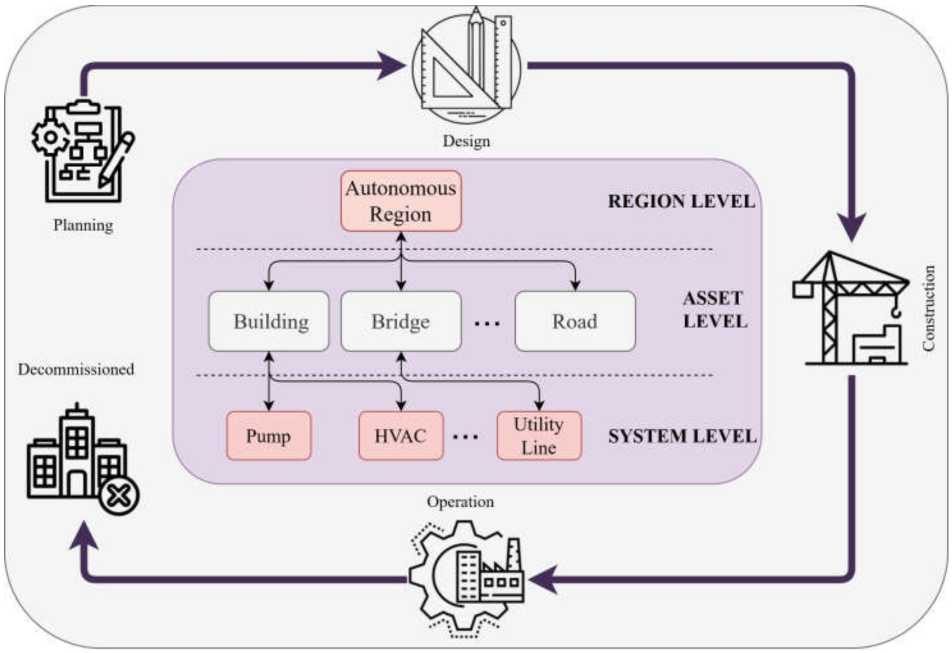

Figure 2 Temporal and spatial connections and hierarchy of modulated DTs

Many of the current DT research has been focused on information construct. In the built environment, however, damage assessment of existing infrastructure and design options of new infrastructure are important in the lifecycle management of region assets. Unlike the production application strategy in manufacturing, a creation application strategy is thus needed for buildings and infrastructure.

Table 2 presents the system architecture of DTs. It consists of five layers: data acquisition, data transmission, model analysis, feature mapping, and users collaboration. First, multimodal data are acquired from remote sensing, in-situ sensing, and nondestructive testing. Subsequently, the collected data are transmitted to a DT curation and storage facility in the region. Following this, the received data are analyzed using informational and computational models. Subsequent to the analysis, the features of interest in asset management and regional planning are extracted and presented in mapping formats in the DTs. Finally, the processed features are communicated with end users through visualizations, dashboards, and interfaces to assist in collaboration and informed decision-making.

Table 2. Five layers in the architecture of DT

Layer	**Key Function**
Data Acquisition	Collection of data from remote sensing in-situ sensing, and nondestructive testing
Data Transmission	Secure transferring of the acquired data from sensors and tests to the DT platform
Model Analysis	Data cleansing and integration to create the virtual representation (or model) of a real world, model analysis to transform raw data into meaningful insights and patterns, and predictive models that facilitate a deep understanding of object or system’s behaviors
Feature Mapping	Feature extractions and their geospatial distribution in a 3D platform of the DTs
Users Collaboration	Visualizations, dashboards, and interfaces that help multiple users at various security levels connect with each other and navigate the DT for controlled data access and manipulation

To exemplify the impact of enhanced DT at the asset level, Section 3 presents the two foundational computation platforms that couple information and computation modeling as well as experimental and computational simulation. Section 4 presents a case study conducted on a university campus scale. This case study serves as a tangible demonstration of the practical application of DT principles within conventional infrastructure. By focusing on a specific campus environment, this study showcases how DT can be effectively employed to realize potential benefits and bring about transformative impacts on system, asset, and regional levels.

3 DT AT ASSET AND SYSTEM LEVELS

While employing computational models is crucial for addressing structural safety concerns, the information modeling of nonstructural components becomes necessary for comprehending the functionalities of a building system. This is underscored by the fact that the integrity of structural components significantly influences the operations of nonstructural elements. Consequently, the synergy of computational and informational modeling is essential for the efficient and effective management of building and infrastructure assets, with updates occurring nearly in real time. As a result, the establishment of two foundational computation platforms is imperative to facilitate the implementation of DTs for both computational and informational modeling:

1. *Spatial connection of structural and nonstructural components*. Current computational and informational modeling tasks are done by two completely isolated technical communities using different approaches. For the development of DTs, the two modeling techniques are transformed into one simple yet effective computational and informational engine to meet the multiple needs in performance evaluation as summarized in Table 1.
2. *Temporal connection between a built facility/environment and a new facility/environment to be built in part or entirety*. This platform plays a critical role in bridging planning, design, construction, and operation of a physical building and infrastructure system.

As previously mentioned, the forefront of DT technology advancement predominantly centers on digital and physical twinning within a single model, such as computational mechanics or information-only domains. To enhance infrastructure lifecycle management at the asset level, it is crucial to integrate computational, informational, and other relevant models. The following two subsections offer practical examples that illustrate the integration of these models.

3.1 Coupling of Computational and Informational Models

A building consists of structural components that primarily resist loading and nonstructural components that support building operation. The nonstructural components are further divided into two groups: A and B. Group A includes the pipeline system, hydraulic elevator system, and beams in the ceiling system, which are significantly interacted with their supporting structural components. Group B consists of the non-beam ceiling system, glazing system, and drywall partitions, which have negligible interaction with structural components.

Figure 3 shows a workflow diagram of the coupled computational and informational modeling to determine the probability of damage states and item costs in structural and nonstructural components. The computational and informational models are integrated into a seamless platform of fiber elements to address both mechanical behaviors (i.e., stress and strain at material levels) using OpenSees computational software and functional value properties (i.e., integrity and cost at component or system levels) using informational interrelation. To maintain simplicity and efficiency, macro-scale models are introduced for nonstructural components and meso-scale models are used for structural components. Specifically, the structural components and Group A nonstructural components are represented by fiber elements in a finite element model (FEM) and analyzed under external loading (earthquake) to evaluate the building responses and damage states. Group B nonstructural components are represented by their informational model for lumped effects to estimate their damage states from respective fragility curves based on the overall performance of the building.

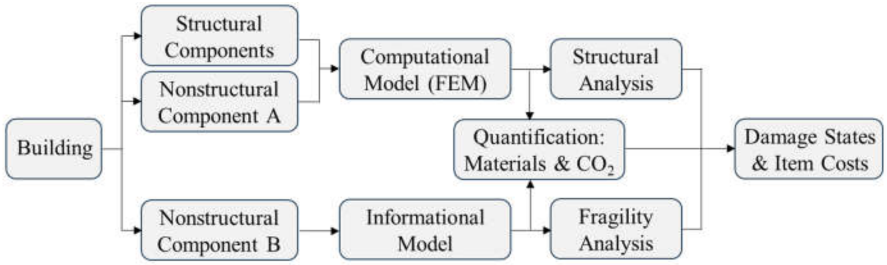

Figure 3 Workflow diagram in damage and cost analysis in structural and nonstructural components

In Group A nonstructural components, the pipeline system was meticulously modeled to reflect the pinching behavior of joints along with their supporting hangers and wire restrainers. Similarly, the hydraulic elevator system was modeled to capture primary types of damage that potentially affect the performance of chassis, cabin, and main supporting cylinder. The beams in the ceiling system were modeled to account for their stiffness and strength effects on the building responses. In Group B nonstructural components, the non-beam ceiling system was modeled in a lumped sum for various failure modes such as the dislodgement of ceiling tiles, loss of connections along the edges, and vertical movement. These types of damage were comprehensively assessed and quantified through the utilization of fragility curves. The informational model for Group B nonstructural components and the size information of the computational model for Group A nonstructural components and structural components include the material data for each component that was used to estimate CO_2 emissions resulting from producing these materials. This quantification was finally employed to determine the component costs under scenario damage states. Overall, the coupled computational and informational model offers a comprehensive dataset detailing the post-earthquake condition of building components and the environmental impact of the materials utilized in the construction of the building.

3.2 Hybridization of Experimental and Computational Models

Buildings and civil infrastructure are commonly instrumented with accelerometers for monitoring structural behavior. However, this method has two notable drawbacks. Firstly, the extensive processing of acceleration measurements is required to derive data related to structural behavior, such as crack width and steel mass loss. This intricate mathematical process often serves as a barrier to the widespread adoption of sensing technologies. Secondly, the deployment of accelerometers relies on the configuration of an entire structure, making it unsuitable for adaptability to partially erected structures or entirely new constructions.

In practice, all stories of a building are typically built with the same materials using the same erection process of prefabricated components during construction. The first story, resting on a rigid base, is often subjected to a larger drift than the second and above. Thus, a novel strategy of hybridizing experimental and computational modeling is proposed in this study, as shown in Figure 4. A structure is divided into two groups: experimental members in the first story and computational members above the first story. The experimental members are modeled by fiber elements and instrumented to measure the load-displacement response of the first story. The material properties extracted from the load-displacement curve are transferred in real time to update the FEM modeling and evaluation of the above stories using computational simulations. This hybrid experimental and computational treatment is compatible with the sequence of construction of a new building. This hybrid modeling strategy bridging existing to new constructions is also more accurate than conventional models. For a four-story, two-bay steel building structure, the hybrid treatment proved at least 25% more accurate than those simulations even from a post-earthquake calibrated model.

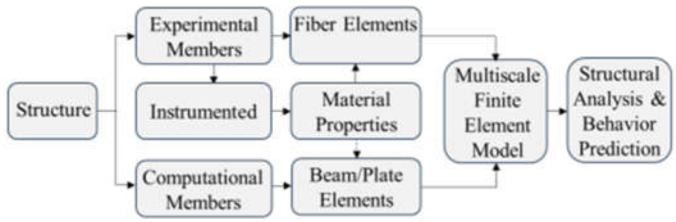

Figure 4 Workflow diagram in hybrid experimental and computational modeling and analysis

4 DT AT THE REGION LEVEL

A case study is presented to unlock potential DT benefits and create transformative impacts on asset management and regional planning of a university campus. Figure 5 shows the 3D rendering of the campus DT over an area of approximately 500m×500m.

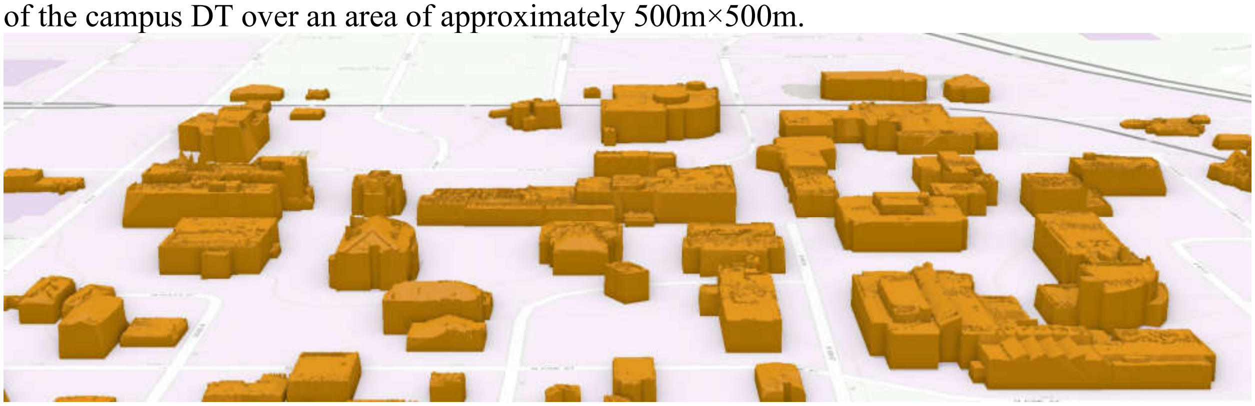

Figure 5 3D rendering of a university campus as a common platform of the DT modules

In this document, the DT expands beyond individual building assets to encompass the entire campus, including buildings, green areas, underground utilities, and other components. This broader scope is termed the DT at the regional level, emphasizing the scale of analysis. However, a closer examination indicates that the DT modules for buildings are at the asset level, while drainage systems can be categorized at the system level. This interconnectedness illustrates the hierarchical relationship between various levels of analysis as illustrated in Figure 2.

4.1 Workflow to Realize Multiple DODTs and Values

As indicated in Table 2, the workflow of creating a digital twin of the campus is shown in Figure 6. It starts with gathering data from various sources such as LiDAR, cameras (infrared (IR), hyperspectral, HiFi RGB), IoT sensors, and GIS databases to ensure a comprehensive and accurate representation. These data are then securely transmitted through robust protocols to a centralized or cloud-based storage platform on which the campus DT is hosted. The LiDAR data is used to generate a Digital Elevation Model (DEM) and a Digital Surface Model (DSM), representing terrain and surface features including buildings. Building extraction is then performed to isolate structures and their features from the DSM. Subsequently, these extracted building footprints are transformed into 3D models using various modeling techniques in the GIS platform. These 3D models are carefully integrated, georeferenced, and aligned within the campus DT, ensuring spatial accuracy and seamless integration. The models are continuously refined and enriched with real-time data to keep it up to date with the changing campus. Features relevant to the built environment are carefully defined within this model. These defined features enable detailed analysis and scenario simulations, presented as DODT, to support campus planning and sustainable decision-making. The created features encompass a broad array of domains, including infrastructural planning, building envelope diagnosis, construction management, responses to extreme events (earthquakes and floods), energy usage, development of green spaces, and security. The insights obtained from these features are thoughtfully disseminated through intuitive user interfaces, enabling stakeholders to navigate and interrogate the campus DT. Furthermore, creating a collaborative environment is crucial, encouraging the active involvement of various stakeholders and experts to embrace diverse perspectives and expertise, optimizing the campus environment's functionality.

It is evident from Figure 6 that the data acquired from an individual sensor is utilized to achieve multiple DODTs. Furthermore, some DODTs are developed using a combination of data from various sensors. Although each sensor's data are initially used independently, the spatial-enabled nature of the multilayer data makes it straightforward to fuse multiple datasets. Combining these fused data with fresh sensor data has the potential to create new DODTs. Additionally, given those data are collected biweekly to update the DT, the time-series data can track changes and utilize artificial intelligence (AI) and machine learning (ML) algorithms to forecast the future. This foresight enables predictive maintenance, which represents another novel DODT.

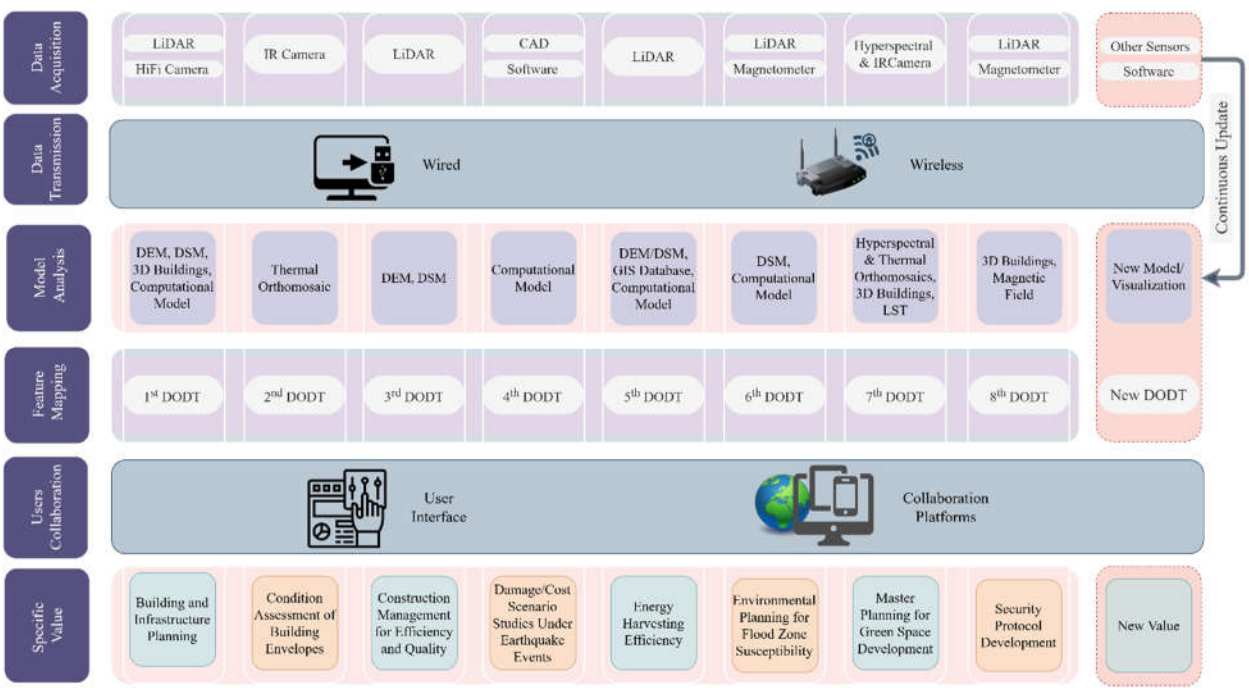

Figure 6 Simplified workflow of the campus-scaled DT modules to realize multiple DODTs

Figure 6 also demonstrates the specific values of the campus-scale DT. These values are realized through digital modeling and analysis. The output of each model and analysis provides a distinct value and is thus considered one DODT. A total of eight (1^{st} to 8^{th}) DODTs are presented in Figure 6. The numbering of the DODTs is presented in no particular order or hierarchy; instead, they are listed in alphabetical order of their values as presented below:

1. Building and infrastructure planning,
2. Condition assessment of building envelopes,
3. Construction management for efficiency and quality,
4. Damage/cost scenario studies under earthquake events,
5. Energy harvesting efficiency,
6. Environmental planning for flood zone susceptibility,
7. Master planning for green space development, and
8. Security protocol development.