# Enabling Digital Twins with Advanced Visualization and Contextualization of Sensor Data with BIM and Web Technologies

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## Abstract
The construction industry is going through a technological paradigm shift due to growing user needs and the demand for a sustainable built environment. The advancement of Building Information Modelling and web technologies allows to integrate heterogeneous datasets and develop innovative user-oriented applications. Several efforts aim at increasing the utilization of BIM and operational building data, but the integration of virtual models and the physical world to enable adaptive interaction and bi-directional coordination is still in its infancy. The Digital Twin paradigm has gained popularity in research, but also faces challenges related to its adoption in the industry. Data visualization within a Digital Twin is significant when communicating complex multimodal data from heterogeneous sources. Therefore, this paper proposes a web-based platform for visualization of spatio-temporal building data to enhance Human-Data Interaction and implementation of Digital Twins in the built environment. The implemented application is tested and evaluated with two use cases and the end user.

**Keywords:** BIM, Internet of Things, Digital Twin, Data Visualization, Human-Data Interaction

## 1 Introduction
Building Information Modelling (BIM) (Borrmann et al., 2018) and emerging technologies are progressively changing the way information in Architecture, Engineering, and Construction (AEC) is generated, stored, and exchanged between stakeholders. Research has demonstrated that the advancement of BIM hinges upon the meticulous consideration of people, processes and evolving technologies in a constantly developing and interconnected world (Batty, 2018).

Even though AEC has undoubtedly benefitted from the progressive technological advances, the productivity rates of the sector are still amongst the lowest in industry. Moreover, the construction industry contributes significantly to global warming and climate change, leading to a growing challenge for a smarter built environment and more determined energy and carbon emissions programs globally. The uptake and integration of BIM, Internet of Things (IoT) and Artificial Intelligence (AI) is demanded to improve energy efficiency and reduce operation costs (Howell et al., 2017). The implementation of Industry 4.0 technologies is also an enabling force that has the potential to revolutionize AEC industry practices.

In that relation, BIM has been utilized to incorporate lifecycle management of built assets, but the current level of BIM is not entirely compatible with IoT integration (Howell et al., 2017). When it comes to its semantic completeness in subjects such as control systems, sensor networks integration, social systems, and urban artefacts beyond the scope of buildings, BIM proves to be relatively deficient. Hence, it requires a comprehensive and scalable semantic approach that can handle dynamic data at multiple levels (Boje et al., 2020).

The intelligent use of IoT data in the design and construction of buildings can improve performance, widen the practicability of systems and improve the management and service capabilities of buildings, thereby enhancing people's quality of life (Kong & Ma, 2020). For example, sensors monitoring building operation and human-made events can provide insights into the current operational status of a building (Petrova et al., 2019) and enable automated fault detection (Stojanovic et al., 2019). Whilst several efforts aim at increasing the use of BIM models, the integration of the virtual models and the physical world to enable adaptive interaction and bi-directional coordination is still in its infancy. To achieve this bi-directional coordination, computational resources are required to securely integrate the virtual and physical domains such as the changes in one environment are autonomously mirrored to the other (Akanmu et al., 2013).

As a result, the Digital Twin concept has recently gained popularity in AEC research. Digital Twins rely on the notion of data-centric management of a physical system (including processes, sub-systems, materials, products, and assets) and aim to capture real-time activity, thereby enabling predictive intelligence for decision-making, monitoring, asset maintenance and control. Despite there not being a commonly accepted definition, Tao et al. (2019) suggest three main constituents of the Digital Twin: a physical asset, its digital counterpart, and the connection between the two. However, despite its potential, the Digital Twin concept faces challenges related to its adoption in the construction industry. These include data integration and interoperability issues, the inability to support design cycles of non-existing assets or processes, as well as how Digital Twins should be implemented in real-time environments. Finally, data representation and visualization to users present another significant issue (Turner et al., 2021).

Turner et al. (2021) state that data visualization within a Digital Twin is significant for communicating complex multimodal data from heterogeneous sources and various sensors to users, mainly because of the limited cognitive bandwidth of humans. Therefore, conveying and visualizing such information in a location- and context-aware manner is key to the successful implementation of Digital Twins in the AEC industry. The visualization has to be accurate, enhance the understanding of the real-world, be specific to different user needs, and aid collaborative consultations and coordination from a functional and ergonomic outlook (Kubicki et al., 2019). Even though the visualization of building models continues to be an issue in terms of the veracity of construction project typologies, BIM provides the means for better visualization, semantic representation of building components and improved level of contextual information.

Therefore, this paper presents a framework and implementation of a web-based platform for visualization of spatio-temporal data (BIM data and operational building data) in a location- and context-aware manner to aid the implementation of Digital Twins in the built environment.

The remainder of this paper is organized as follows. Section 2 outlines the methodology adopted in the study. Section 3 presents an overview of the related contributions within data visualization for Digital Twins. Section 4 and 5 discuss the proposed system architecture and its implementation in two use cases. Finally, Section 6 concludes the article.

## 2 Methodology

The study is motivated by the need of AEC stakeholders to interact with and reuse multimodal data in Digital Twins in decision-making. Therefore, this effort takes an outset in Digital Twins, data visualization and contextualization, Human-Data Interaction (HDI) and User-Centered Design (UCD). The main methodological approach relies on the combination of Contextual Design (Holtzblatt & Beyer, 2017) with the Five Spaces of Cognitive System framework for data visualization (Sedig and Parsons, 2016). The study adopts these two approaches in an integrated manner to achieve a cohesive framework and system implementation that consider both the end user and the relevant data visualization aspects.

The Contextual Design method consists of two major sequences – I. Requirements & Solutions, II. Define & Validate Concepts. The first sequence aims to acquire information about the users' daily practices, organizational workflows, and preliminary ideas for the new solutions. The second one aims at advancing design proposals towards more refined abstractions of relation and interaction with information and between users. The Five Spaces of Cognitive System is a systematic approach accommodating the development of interactively aided data visualization tools. It allows identifying sources of data information, computing capabilities, and assessing ways of representing data and interaction patterns with which users will perform their activities.

In the context of this study, Contextual Design is applied as the main methodology for user processes identification and solution development, particularly considering user-data interaction in the context of Digital Twins. Additionally, the Five Spaces of Cognitive system is the main framework used for the development and implementation of the proposed system architecture, including applications, libraries, services, sensors, and actuators, etc., which can be tailored to the specific use case whilst preserving the structure of the framework itself.

The end user with whom the contextual inquiry has been performed is a large engineering consultancy organization focusing on building energy design and engineering. BIM models and indoor environmental quality sensor data necessary for the evaluation of the platform have been provided by the end user. Furthermore, the developed web platform has also been tested with two different use case buildings.

## 3 Data visualization and Human-Data Interaction in the context of Digital Twins

Hegarty (2011) covers the subject of cognition in the design of visual representations and defines three visual display categories: (1) iconic, which aims to represent an entity placed in the physical world and its properties, e.g., 3D building models, connections between rooms in facilities, etc.; (2) relational displays, showing relationships between factors and properties, which are not present or visible in the represented object, e.g., the temperature in a room; and (3) a hybrid of the first two, allowing to allocate invisible properties on the visual-spatial object, e.g., temperature heatmap overlaying rooms, enabling context and depth of cognition (Hegarty, 2011).

Visual representations can augment the perception of data and enable allocating more resources to the external representation (knowledge about the environment, its constraints and properties that can be retrieved with perceptual processes) rather than internal (schemas and meanings of objects where cognition is used to retrieve necessary information). Together, they create distributed representations (Zhang & Norman, 1994). Bringing represented models closer to the mental activities is important for allocating more mental space for interaction (Sedig & Parsons, 2016).

In terms of data, visualization can be divided into static and interactive (Sedig & Parsons, 2016; Veglis, 2017). Static data visualization uses schemes and views that have been predefined by the designer (developer). While it can be useful in some areas, it has shortcomings, such as fixed data selection, data types, range, 2D-only perspectives, etc. (Ward et al., 2015). In the built environment, the relationships between different data types and data structures are getting more complex, and data velocity and volume are increasing rapidly. That poses higher requirements to data visualization and interaction so that the value in data can be uncovered for end users. Thus, static visualizations are being replaced by interactive approaches (Kim et al., 2017; Natephra & Motamedi, 2019a). By using interactive approaches, a user can contextualize given information, dynamically adjust it to different perspectives and sub-visualizations, making it faster to process computationally and mentally (Sedig & Parsons, 2016). To obtain a complete picture of the state of certain situation, outcome, prediction or simulation result, the end-user has to interact with and use various datasets, or even the same datasets, but presented in different ways (Chang et al., 2018). Interactive data visualization enhances the analysis, process, and complex activities, especially in the age of big data, which has to be properly aggregated and visualized (Dou et al., 2020; Po et al., 2020).

In AEC, data is usually derived from heterogeneous sources (requirements, simulations, sensors, building management systems, etc.), which should be correlated to existing BIM models, be consistent across project models and documentation, as well as with the temporal dimension (Boje et al., 2020). The pursuit of 3D BIM real-time visualization occurs due to the communication requirements between several actors in the AEC industry (and beyond) (Dave et al., 2018).

Integrating IoT deployment in the built environment and developing user interfaces is a major challenge in the construction industry (Dave et al., 2018). Therefore, to experience the full potential of BIM and satisfy the ever-increasing user demands, other technologies should be implemented supplementing BIM technologies.

There is a requirement to address the demand for the integration of sensor data and digital representations of the built environment for fostering stakeholder collaboration management within the area of Real Estate 4.0 and Facility Management (FM), particularly in a spatial representation context (Stojanovic et al., 2019). In terms of visualization, a Digital Twin's purpose is to create high-fidelity visual representations and simulations using data and models containing geometric shape, rules, behaviour, and new constraint models (Tao et al., 2019).

The effectiveness of the Digital Twin is based on the capability and viability to retrieve data and semantics accurately and make the accurate data sets available for processing (Boje et al., 2020). On the other hand, decision-making is strongly dependent on how humans obtain information, compare it, and make a final selection (Jin et al., 2019). Providing a user-driven experience is necessary, as the Digital Twin should deliver to various requirements and engage with end-users to assist holistic decision-making (Boje et al., 2020).

## 4 Proposed system architecture

Even though the framework focuses on developing data visualization and interaction mechanisms for end users, the system architecture also serves the data contextualization needs and adheres to the other components of the Digital Twin concept. The use of a web-based solution substantiates that the proposed framework can be further aligned with other components such as actuation, monitoring etc., to become a fully integrated Digital Twin.

The system architecture is divided into the proposed Five Spaces of Cognitive System (Sedig & Parsons, 2016) to create a holistic understanding and division of technical components that respond to the user needs through relating to these spaces (Figure 1). The proposed system adheres, therefore, to the following defined spaces: *Information Space*, *I. Computing space – indirect alternative (use case determined)*, *II. Computing space – direct alternative (desired), Representation Space, Interaction Space* and *Mental Space*. The five spaces support the execution of the main steps of data acquisition and storage; data manipulation and refinement; data integration and contextualization; sensor data representation in BIM models; representation and visualization of data on the web; as well as enabling Human-Data interaction through a dedicated web platform and user interface. The implementation of the spaces is elaborated below.

### 4.1 Implementation

#### 4.1.1 Information Space

The *Information Space* (bottom in Figure 1) contains two subspaces. The first subspace is the *Information collecting space* that encompasses two layers. The first layer is the *Perception layer* which consists of physical objects such as sensors and monitoring devices capturing the values of different observed variables in the physical environment (e.g., temperature, $CO_2$, humidity, etc.). The second layer is the *Network layer*, which is connected to the Internet and transmits the collected data to the *Data system* in the *Information transfer & Computing space* (second subspace of the overarching *Information Space)*. In the second subspace, *Information transfer & Computing space*, the data is stored on the cloud which can process the large amount of continuous data on distributed servers.

#### 4.1.2 I. Computing Space - indirect alternative (use case determined)

The *Computing Space* (lower and middle parts of Figure 1) has four main layers: *Data acquiring, Data storage, Data refining, and Backend/frontend* stack for web development. The division of the *Computing Space* into *I. Computing Space – indirect alternative (use case determined)* and *II. Computing Space – direct alternative (desired)* is directed by the way collected operational building data is provided to the computing space. This study considers two main scenarios (also tested in the use cases in Section 5), namely (1) sensor data is provided in Comma Separated Value (CSV) format and (2) sensor data is available behind an Application

Programming Interface (API). The system can handle both options relative to the particular use case, but *II. Computing Space – direct alternative*, where data is accessible via an API, considers the state-of-the-art data handling approaches and is also desired by the end user. In both scenarios, cleaning and refining of the sensor data are implemented using the pandas data analysis library, an open-source data manipulation and analysis tool built on top of the Python programming language.

In *I. Computing Space – indirect alternative*, after refinement, the sensor data is converted to JavaScript Object Notation (JSON), which is necessary for the further implementation of the web platform, i.e., for creation of key-value pairs of information which can be linked to 3D BIM models in Autodesk Forge, allowing sensor observations and values to be visualized both in charts and in 3D BIM models. In terms of sensor data visualization and contextualization with BIM models, if the BIM model does not contain all necessary information, e.g., relations between sensors and rooms/spaces, or no sensors, it needs to be adjusted. This can be done using Dynamo for Autodesk Revit – a visual programming tool developed for Revit and using Revit's API. Developing the script using Dynamo allows to place objects in the model under set conditions and change parameters using tables with room-sensor relations. The model, thereafter, is translated via a Forge extension in Visual Studio Code (VS Code) using Model Derivative API. Finally, the refined and converted to JSON sensor data is placed in a code repository in Visual Studio Code IDE (Integrated Development Environment) and is linked to the data visualization extension in the Forge platform and to JavaScript libraries such as Chart.js, Highcharts.js, etc., that allow the implementation of interactive charts in web pages (lower part of Figure 1).

#### 4.1.3 **II. Computing Space – direct alternative (desired)**

In this case (middle in Figure 1), the sensor data is collected in the *Data acquiring* layer from the *Information transfer & Computing space* through an API call, specific to the sensing or actuating devices. The acquired data is stored in the NoSQL database MongoDB with the help of MongoDB stitch libraries which are JSON based, and data can be fetched through an API service.

In terms of primary and server-side support for the development of the web platform for BIM and sensor data visualization, Node.js (JavaScript runtime environment enabling frontend and backend of applications) with npm (package manager for Node.js), and Express (Node.js web application framework) were utilized. For supporting the frontend, JavaScript with jQuery were mainly used. However, it is possible to adjust and wrap the code in the React[1] or Angular[2] frameworks. The recommendation for further research here is to examine different kinds of languages and IDEs (Go, .NET Framework), frameworks (React, Angular, Vue.js), databases (Cassandra, CouchDB), and how they suit and with current and future needs.

#### 4.1.4 **Representation Space**

*The Representation Space* (above middle in Figure 1) contains the Server side and the Client-side layers. The Server-side is responsible for handling authentication, connection to BIM360 cloud server, and translation of BIM models from supported source formats into SVF/SVF2 (Streaming Viewing Format) using Model Derivative API to render a model on the website.

The Client-side relies on frontend web development tools that can project the User Interface (UI) and viewer through which the end user is going to interact with the system. The core of the Client side is Viewer (client-side library), which custom-made extensions (e.g., toolbar, sensor-data heatmap) can complement. Visualization and interaction models are incorporated in the *Representation Space* to develop proper visualization patterns or structures and means for interacting with data via model or graphs leveraging micro and macro levels of interactivity.

Even though interaction models would belong to the space above, it is done in such way to emphasize the significance of emerging interactive data visualization in the AEC industry.

#### 4.1.5 **Interaction and Mental Space**

The *Interaction and Mental Spaces* (top in Figure 1) are closely connected and create a "flow" through the *Representation space* – there is no solid boundary.

[1] https://github.com/Autodesk-Forge/forge-react-boiler.nodejs
[2] https://github.com/theNBS/ng2-adsk-forge-viewer

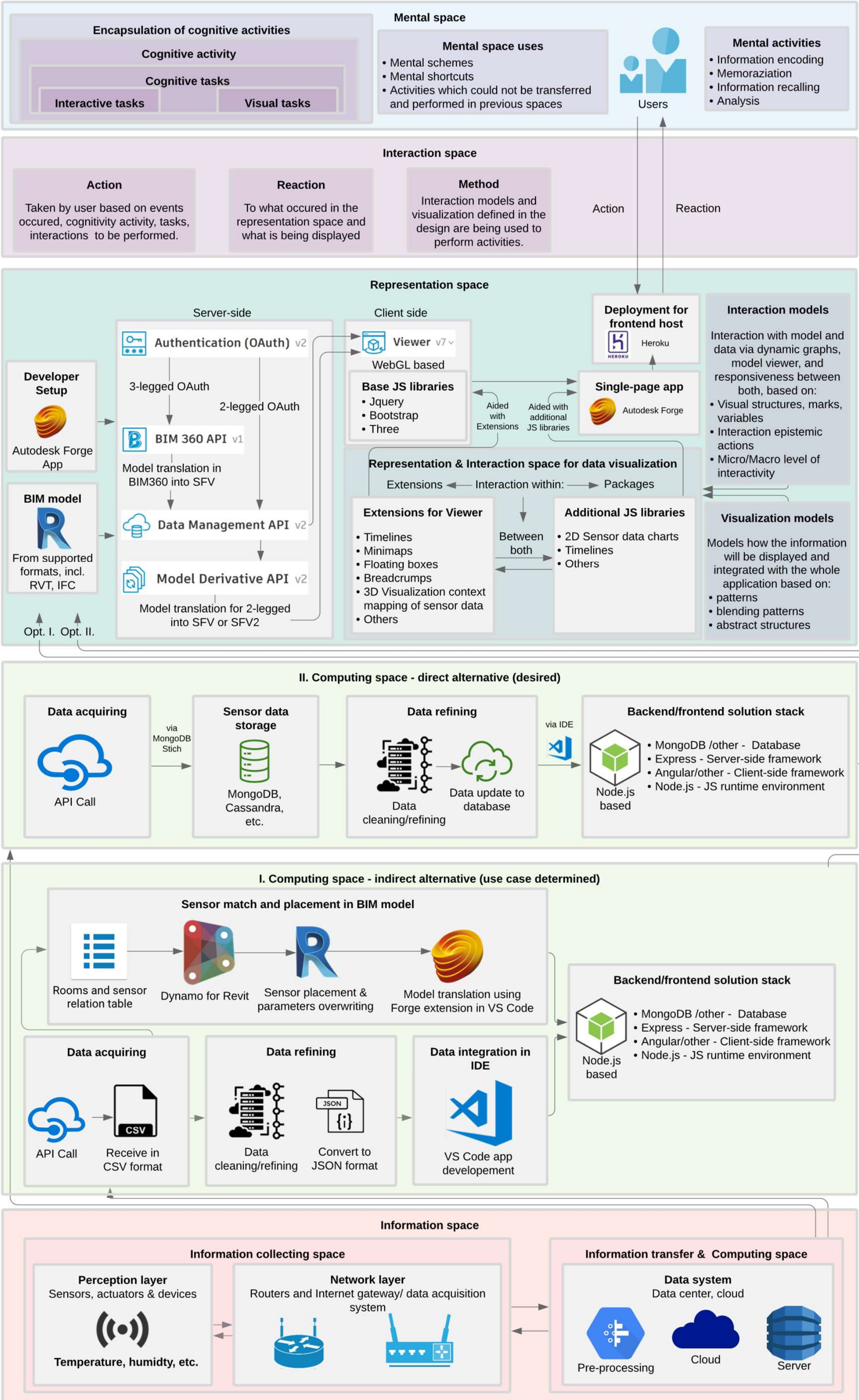


**Figure 1.** System Architecture proposal ecompassing Five Spaces of Cognitive System.

The *Interaction Space* evokes Reaction (the user reacting to events and data shown in the Representation space) and Action (the user leading the initiative). The main medium in *the Interaction Space* are Interaction models and Visualization models that power the *Representation space*. In the scope of whole system architecture, the *Interaction Space* acts as a bridge between the *Mental Space* and *Representation Space*. There are three levels of interaction – low (detailed, specific, e.g., button clicks), intermediate (broadening the abstract level of exploration, e.g., selecting, connecting, navigating), and high (complete abstract concept of reasoning and relating to mental models) (Tominski, 2015).

The *Mental Space* is, therefore, more abstract and is directly related to perception, cognition and decision making. The crucial aspect of the *Mental Space* is that it initiates with Cognitive activity, through Cognitive tasks, and decomposes to Interactive and Visual tasks. This space also uses mental shortcuts (heuristics). The more activities are delegated to the *Representation and Computational Spaces*, the less intensive the user's mental activity.

## 5 Testing and evaluation

Two use cases were used to test the implemented system architecture. In both use cases, the intention is to visualize and contextualize the sensor data of the building in operation in the web platform allowing the user to perceive and interact with it in various ways. That requires each building to have both a 3D representation in representation medium (a software with compatible 3D kernels, or web-oriented library for 2D/3D rendering) and sensor data acquired from corresponding sensing devices in the building, which can be also visualised in the 3D model.

### 5.1 Use Case 1

In the first use case, the BIM model of one floor of the BloxHub building located in Copenhagen was utilized. Each area contains a wall-mounted wireless sensor capturing the values of indoor environmental quality observations, i.e., temperature, humidity, $CO_2$. Historical sensor data are provided in CSV format with sensor values and timestamps. In the BIM model, the sensor objects were already accurately placed on the wall, and their custom ID parameters correlated with alike parameters of Room (Revit elements) objects. As the CSV data was accurately related to the Room objects of the BIM model, it is possible to convert CSV data files into JSON format and place it directly into the repository. After that, the BIM model in Revit (RVT) format (one of many source formats) is translated into SVF2 (extension of SVF), using Forge extension for VS Code, to be readable by Forge Viewer and ultimately viewable in modern web browsers. The key aspect is to use SVF2 over SVF to optimize viewable, editable performance of 3D objects and use "Generate Master Views" to include Rooms and properties. Otherwise, only room boundaries are generated.

For the development with the MEAN (stack for backend/frontend (*Computing Space*), a file structure is necessary and different packages of the components are required to be installed through the IDE to develop a real-time connection to the web and for running, debugging, and testing the code. For viewing the model in the browser and setting up the environment on the web, a designated web server is required. This is achieved directly in the IDE as part of the MEAN stack, where Node.js is used for the connection. Furthermore, the implementation relies on npm packages (specifically npm packages for Express, multer for file uploads and Forge API packages). Through these steps, a JSON file is created with references in start.js, launch.js and config.js, which contain components to run and debug the models accurately in the browser through the viewer API. For accessing the model derivative API, buckets need to be created to extract the geometry and metadata of the BIM model. For the client-side viewing and custom web design, an HTML component and CSS file containing the script is required.

The first prototype[3] of the UI of the web application is shown in Fig.2. The forge viewer API makes it possible to display the translated model, and the reference to the Uniform Resource Name (URN) selects the precise file for the translation process to the SVF format. The viewer API has basic toggle options to rotate the BIM model and select elements. On ticking the tabs, it adds the extension selected in the extension bar, which creates a window of the extension on click.

[3] https://github.com/qwe0254/Forge_Hack

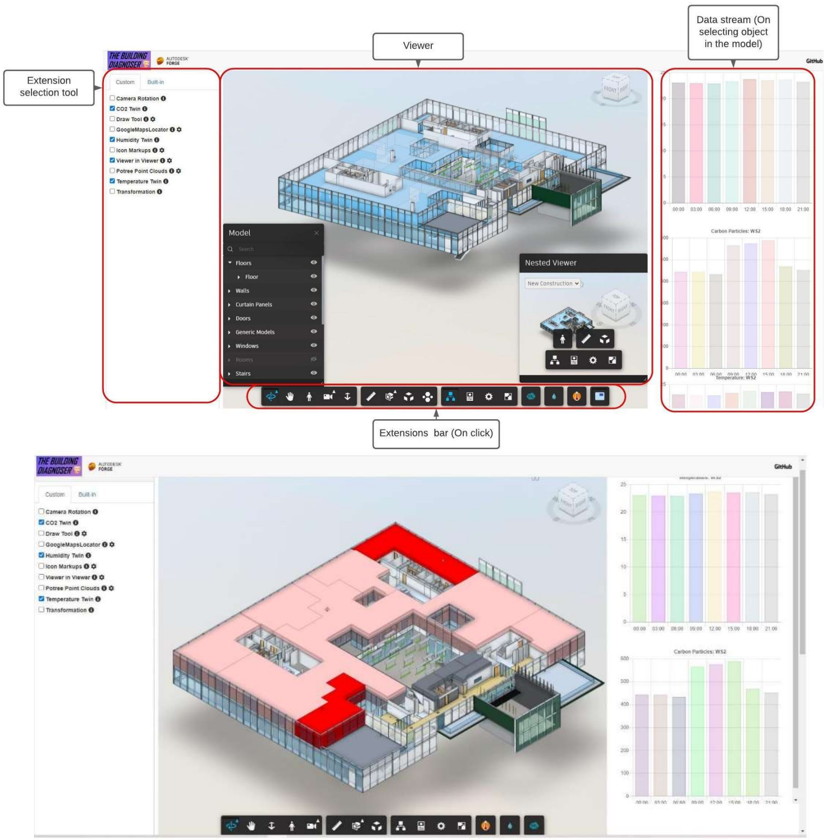


**Figure 2. a)** The main interface of the web application (top) **b)** Visualisation of sensor data directly in the BIM model and as a heatmap and in graphs (bottom)

A data stream dashboard displays the sensor data values and the time from the *sensordata.json* file in a bar chart (right in Fig. 2a). There are three extensions for visualization of sensor data, i.e., temperature, $CO_2$ and humidity. The icons are added through the HTML script for the front end of the UI, as seen at the bottom right in the extension bar panel. For each sensor data value, a button was created for the user to select and visualize the needed data with designated colour schemes, while accurately relating the values to the specific spaces (right in Fig. 2a).

## 5.2 Use Case 2

The second use case uses different BIM model and sensor data. This makes it possible to see which steps could be reproduced in any scenario, which steps are useful only for the singular case, and what improvements could be made to address modularity, scalability, and universality. In this case, the BIM model and sensor data were provided by the end user that the contextual inquiry was performed with. The BIM model is a building from a "Healthy Homes" project, where sensors are placed in three apartments to monitor the indoor environmental quality. The purpose is to understand and evaluate changes in the indoor climate and find an efficient way of sharing sensor data in an accessible way with other stakeholders, supported by the contextualization capabilities of 3D BIM models. Learning from the first use case, a few aspects had to be checked before uploading the 3D model into the Forge Viewer. For instance, the BIM model was provided with room names and numbers (embedded in Revit Room properties), sensor data (CSV files), and a corresponding list of relations between rooms (XLSX file with room name, number, and related sensor ID). The evaluation of the room information consisted of: A) which rooms in Revit are listed in the Excel table; B) which rooms are omitted; C) are there any errors with the listing.

Since the rooms and corresponding sensors are given in XLSX format, the challenge is to place the sensors in the related Rooms and attach a correct sensor ID to each Room. This step is performed with Dynamo for Revit. Attention needs to be paid to potentially problematic areas, such as multiple sensors being linked to the same room. Multiple sensors can be linked to the same space; however, that proved to be an inconsistency, which was eliminated. Furthermore, the sensor data was treated to eliminate inconsistencies with the method described in 4.1.2., i.e., using the pandas library to clean and refine the data and ultimately import it to JSON. The JSON format is flexible when it comes to linking the sensor data with the BIM model in the Forge Viewer.

### 5.3 Validation with the end user

The initial validation of the results was performed in a feedback session with the end user. The functions of the prototype were deemed satisfactory, but the end user also indicated a need for continuous update of heatmaps, observed variables (e.g., temperature values) directly in the BIM model when specific rooms are selected. The company also requested an option for selecting a timeline for each selected space/room. Thus, these functionalities would be incorporated in the next implementation iteration. To test the application, the end user uploaded another model and data into the prototype, as the intention is to use the developed solution as a universal tool in projects. It was possible to enter new datasets and models; however, it has to be noted that data refining in the Computing Space of the system architecture is specific for the sensor data provided in each use case. Automating data structuring depends on the acquired dataset, which varies from project to project. If there are inconsistencies, then a custom Data refining method must be implemented according to inconsistencies identified from the sensor data or the BIM models.

## 6 Conclusion

This study proposes a web-based platform for visualization of spatio-temporal building data to enhance the Human-Data Interaction and implementation of Digital Twins in the built environment. Based on a literature review and interviews conducted with industry representatives, it is validated that there is a need to cater to the visualization demands for different end users, and to the Digital Twin paradigm, respectively. The interpretation sessions and Contextual Design methods assist in the identification of the user processes. The contextual inquiry confirms the need to contextualize BIM and indoor environment data to provide end users with a visual interface and foster understanding of information between project stakeholders.

The proposed system architecture is implemented as Five Spaces of Cognitive System to create a holistic understanding and division of technical components that respond to the cognitive needs of the user relating to these spaces. The first working prototype of the web application is tested with two use cases and evaluated by the end user (engineering consultancy company). An essential element of a Digital Twin infrastructure is the actuation and bi-directional communication between the digital representation and the physical world. The proposed architecture is intended to work as a framework to implement the visualization needs for developing a Digital Twin based on a user-driven and iterative approach congruent to the technical requirements. With that, the aim of this study is to respond to the Human-Data interaction needs and the implementation of a bi-directional Digital Twin is out of the scope.

The results show that despite the complexity of the system and the large variety of knowledge areas and steps required (e.g., sensor data acquisition, refinement, and representation; BIM model preparation; implementation with a compatible 3D viewer; data and API handling, UI/UX design and development, etc.), the proposed system can respond to the needs for dynamic visualization of operational building data in BIM models. The study shows that data refinement is vital. It must be ensured that there are no errors, empty records, or duplicates of sensors, rooms or other linked items. Correction of sets and relationships and data curation is almost always necessary. Even though data visualization and contextualization are only a part of the Digital Twin paradigm, its successful implementation in the industry hinges on the effective connection of sensor assets, real-time operational building data and BIM models with web technologies. Future work can consider further work modelling sessions to attain feedback and achieve a complete solution catering to both end-user and project stakeholder needs, as well as to visualization, contextualization and data integration needs of bi-directional Digital Twins capable of actuation.

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