LIGHTHOUSE PROJECT #1: MONASH INNOVATION LABS DIGITAL TWIN (MIL-DT): DESIGN, DEVELOPMENT AND CASE STUDIES

FINAL REPORT

Australian Government
Department of Industry, Science and Resources
Cooperative Research Centres Program

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CONFIDENTIAL:	☐ Yes X No
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Date of this report:	1 November 2024
Project completion date:	6 August 2024
Program Leader reviewer:	Duncan Maxwell
Project title:	Monash Innovation Labs Digital Twin (MIL-DT): Design, Development and Case Studies
Project duration:	12 months
Partners:	• Amazon Web Services • Monash University
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Ethics approval details (if relevant)	MUHREC-36215
Acknowledgements:	The authors gratefully acknowledge the support from Building 4.0 CRC and the industry partner, Amazon Web Services (AWS). This research has been assisted and guided by Chris Mano, Craig Lawton and Bobbie Couhbor from the AWS.

EXECUTIVE SUMMARY

Introduction

A digital twin (DT) is a live digital representation of a physical asset throughout its lifecycle. This digital model is updated from real-time data and uses simulation, machine learning and reasoning to help with decision-making. While DTs have been used in product management and manufacturing for over 20 years, their application in the Architecture, Engineering and Construction (AEC) industry is relatively new.

DTs hold the promise to revolutionise the industry by transforming how we design, build and operate the built environment, by enhancing the sustainability, efficiency and resilience of buildings and infrastructure. However, several challenges must be addressed for widespread adoption in the AEC industry, including:

- ensuring networking and connectivity between various technologies
- integrating and analysing diverse data
- managing the complex interactions between humans, the environment and physical and cyber infrastructure.

This report presents the best practices in designing, developing and operating a DT for building operation applications, providing evidence-based guidance for future DT applications. This report starts with a literature review and analysis of DTs developed for building operation applications worldwide. Then, the report outlines the entire design and development processes of a recent DT for the Monash Innovation Labs (MIL), with regard to the system architecture and key functional components configured in response to stakeholder requirements. The benefits of the Monash Innovation Labs Digital Twin (MIL-DT) were explored in this project through case studies focusing on energy-efficient heating, ventilation and air conditioning (HVAC) control and individual thermal comfort analysis, respectively. Finally, this report concludes with key insights and lessons learned from MIL-DT, and suggests a DT design and development framework and future research directions.

Literature review

Through a systematic search of academic literature on the design and development of DTs for building operations, we identified 32 DTs that were well-documented and physically deployed in a built facility. These DTs were thoroughly analysed and compared with regard to data collection, data handling, target applications, scale and stakeholder engagement. This analysis provides a comprehensive landscape of the most recent developments and technologies employed in DT for building operations. In addition, this review offers invaluable insights into the current knowledge and practice gaps in this domain. These gaps include the following.

- Real-time data handling in Building Information Modelling (BIM) platforms like Autodesk Revit is limited, posing challenges for applications needing up-to-date information. Advanced data handling solutions, including middleware, cloud and edge computing, are needed to integrate real-time data from diverse sources. Machine learning and AI can enhance data analysis, providing actionable insights.

- Tracking occupant behaviour is crucial for optimising building operations, but current methods are underdeveloped. Advanced sensors and data analytics tools, including computer vision, can capture and interpret occupant behaviours, improving comfort, safety and energy efficiency.

- Stakeholder engagement is essential for developing practical DT solutions. Early and continuous collaboration ensures user-centric designs. However, short-term projects often lack sustainability, and continuous feedback mechanisms are needed for iterative improvements.

- Privacy and ethics protocols are often inadequate in DTs. Implementing privacy-preserving methods like data anonymisation and encryption can enhance data security and user trust. Integrating these methods into DT systems is crucial for ethical data management.

The Monash Innovation Labs Digital Twin

Located at Monash University's Clayton campus, the MIL is a newly retrofitted, multi-story facility featuring state-of-the-art laboratories, workshops, modern offices and collaborative spaces. To establish MIL as a world-class hub for research and innovation, the Building 4.0 CRC project team at Monash University created a DT of the facility in collaboration with Amazon Web Services (AWS). The MIL-DT is underpinned by a 5-layer architecture (i.e., data acquisition, communication, data-model integration visualisation and applications layers) and enabled by 5 key functional components, including as-built high-fidelity digital building models, multimodal sensing network, data engineering and analytics platform, domain-specific data analytics and simulation, and spatial data visualisation and interaction.

In developing MIL-DT, an agile framework was used to ensure flexibility, collaboration and rapid delivery. The cross-disciplinary team included a project manager, technical specialists, an academic advisory group and a DT user group. The project manager oversaw the plan and facilitated communication. Technical specialists from Monash and AWS designed the system architecture. Academics ensured the solutions were novel and relevant, while the DT user group advised on use cases. A series of workshops were conducted to clarify user demands, refine objectives and solicit feedback. Development occurred in 3 phases of different scales and complexity to ensure robustness and scalability.

Case studies

Effective HVAC control is crucial for building energy efficiency and sustainability, reducing energy consumption, operational costs and greenhouse gas emissions while improving indoor air quality and occupant comfort. A case study investigated the effectiveness of a DT-based HVAC control strategy that adjusts based on real-time occupancy from the MIL-DT. The experiment showed that using DT-based control, which adjusts the fan operation and temperature deadband based on occupancy, resulted in significant energy savings. On days with DT-based control, heating energy load and fan energy consumption were notably lower compared to traditional control days. The average daily energy savings in the MIL lab room was approximately 5 kilowatt hours (kWh), translating to potential savings of around 18 megawatt hours (MWh) for the full heating season. If adopted across Monash's campus, this approach could reduce total heating energy consumption by approximately 735 MWh per year, representing a reduction of more than one-third from the 2,000 MWh baseline.

Workplace safety and health are critical concerns identified by asset managers and building users. Unsafe behaviours, such as violating lab protocols and ergonomic hazards, can compromise safety. Traditional safety management methods, like periodic training and self-reporting, are often inconsistent and unreliable. MIL-DT addresses these issues by detecting and analysing unsafe behaviours using skeleton data from images and videos. Incidents such as eating or drinking near a machine and bending the back when lifting heavy loads were successfully identified and recorded by the MIL-DT. This approach ensures a safer working environment through targeted interventions and real-time monitoring.

Thermal comfort is defined by an occupant's perception of their environment. MIL asset managers and users are interested in thermal comfort data to improve occupant satisfaction and energy efficiency. Traditional methods, like subjective reporting and wearable sensors, are effective but disrupt daily routines and can't support real-time decisions. The MIL-DT adopts a privacy-compliant computer vision method to identify clothing types and actions based on skeletal postures, allowing individual-level Predicted Mean Vote (PMV) calculations. This includes environmental variables like temperature and humidity. Results are visualised on a platform, showing occupants' locations and personal PMV. This tool aids real-time decision-making, personalised recommendations and high-quality research data collection.

Originality and innovation

Building upon existing knowledge and practices of DTs, the MIL-DT aims to push the boundaries of DT functionality and applications in building operations. The originality and innovation of MIL-DT lie in three key aspects:

Sophistication and Coverage: MIL-DT is one of the most advanced DT implementations globally, in terms of both the floor area covered and the extent of sensor instrumentation. This extensive and multimodal sensor system enables the project team to explore various case studies and develop custom-built solutions, demonstrating the benefits and impacts of MIL-DT on critical building operation and management applications.

Adaptive and Scalable Infrastructure: The hard and soft infrastructure that empowers MIL-DT (e.g. sensor system, database, dashboard and visualisation tools) is designed to be adaptive and scalable in size and complexity. This adaptability significantly enhances the potential for deploying MIL-DT's functional components to other buildings and assets.

Interdisciplinary Development and Open-Source Approach: The development of MIL-DT leverages multi-disciplinary expertise in machine learning, IT and engineering. This approach has allowed the project team to create various custom-built solutions using completely open-source toolkits. By avoiding reliance on proprietary vendors, MIL-DT significantly increases its versatility when interfacing with other systems, such as building management systems and supervisory control and data acquisition systems.

Lessons learned

During the development of MIL-DT and the implementation of the functional components, the project team faced numerous challenges and opportunities, leading to valuable learning experiences. Key lessons and insights were gained in areas such as user engagement, data mapping, and privacy and ethics considerations, providing a useful guide for future DT initiatives.

Proactive and Continuous Stakeholder Engagement: The most significant lesson was the importance of user feedback in shaping the DT's design and functionality. Engaging stakeholders early and seeking their feedback at multiple stages helped identify key demands and development priorities, resulting in a user-centric design and efficient development process. This iterative approach allowed for continuous improvement based on real-world usability, ensuring the application met diverse user needs. Regular feedback sessions and user testing were crucial in fine-tuning the system, making it more intuitive and responsive.

Flexible Visualisation Tools: The integration of various data representation methods highlighted the need for flexibility in visualisation tools. Different stakeholders require distinct ways to visualise and interpret data based on their roles. By accommodating these needs, the project ensured effective decision-making and workflow optimisation for all users. This adaptability also allowed the DT to be updated and expanded as new requirements emerged and technologies evolved, enhancing its longevity and relevance.

Consistent Naming and Mapping Approach: Harmonising naming conventions and implementing a standardised spatial mapping approach for sensor data were essential. Accurate spatial mapping is vital for applications like thermal comfort analysis and safety risk detection. A unified naming convention and standardised mapping improve data integration, reduce errors and enhance system reliability, simplifying data analysis and reporting.

Privacy and Ethics Considerations: Monitoring building users requires careful management to ensure privacy and ethical standards. The project prioritised ethical considerations, implementing a privacy-compliant framework to de-identify individuals and conceal their appearance using advanced computer vision techniques. Transparency with users about data collection practices was crucial for building trust. This dual focus on technology and transparency ensured the DT served its purpose without compromising user privacy or ethical standards.

Future research directions

Future research should focus on integrating generative artificial intelligence (AI) into DT systems for data querying and anomaly detection. Generative AI can translate natural language questions into machine-understandable queries, making DT systems more accessible to non-technical users and enhancing their usability and effectiveness. Additionally, developing advanced user interfaces using augmented reality (AR) and virtual reality (VR) technologies can provide immersive experiences, allowing users to visualise and manipulate DT data in real time. For example, AR can superimpose data or simulation results, like heatmaps, onto real-world locations. This helps users, such as building managers, identify issues like excessive energy use and take immediate corrective actions.

Beyond the applications explored in this project, DTs have potential in areas like emergency egress prediction and assistance. DTs can enhance current egress models by providing accurate, real-time data on occupant locations and movement patterns. This allows for dynamic and precise modelling of emergency situations, leading to more effective evacuation instructions. To advance this application, DTs should integrate with building security systems to fetch real-time status data, such as smoke alarms and exit availability. This integration provides a comprehensive overview of emergencies, enabling informed decision-making and efficient evacuations.

LIST OF ACRONYMS AND ABBREVIATIONS

AEC	Architecture, Engineering and Construction
AI	artificial intelligence
API	application programming interface
AR	augmented reality
AWS	Amazon Web Services
BAS	building automation system
BIM	Building Information Modelling
BMS	business management system
CNC	computer numerical control
CV	computer vision
DT	digital twin
IEQ	indoor environmental quality
GAN	generative adversarial network
HVAC	heating, ventilation and air conditioning
IoT	Internet of Things
kWh	kilowatt hours
LiDAR	light detection and ranging
LoRaWAN	long range wide area network
MIL	Monash Innovation Labs
MIL-DT	Monash Innovation Labs Digital Twin
MQTT	message queuing telemetry transport
MWh	megawatt hours
PM	particulate matter
PMV	Predicted Median Vote
SDK	software development kit
STEM	Science, Technology, Engineering, Mathematics
UWB	ultra-wideband
VAE	variational autoencoder
VR	virtual reality
WSN	wireless sensor network

1. PROJECT OVERVIEW

Recently introduced to the AEC industry, DTs hold the promise to revolutionise the industry by transforming how we design, build and operate the built environment, including buildings and infrastructure. In its simplest form, a DT is the live digitisation of the operation and maintenance of a physical asset throughout its life cycle. This technology enables real-time control of a physical asset through a digital interface, allowing for the monitoring of past and present operations and making intelligent predictions about future operations.

DTs have been actively used in product management and manufacturing for over 20 years, where they have proven their value in enhancing efficiency, reducing costs and improving product quality. However, the application of DTs to the built environment is a relatively new field of research and practice. This emerging application holds significant potential to improve the sustainability, efficiency and resilience of buildings and infrastructure.

The benefits of DTs in the AEC industry are manifold. They can provide detailed insights into the performance of buildings, enabling proactive maintenance and reducing downtime. DTs can also support the optimisation of energy use, enhance occupant comfort and improve safety by predicting and mitigating potential risks. Further, they facilitate better decision-making by providing a comprehensive view of the asset's condition and performance over time.

Despite these promising advantages, many critical challenges must be addressed before the confident uptake of DTs can be achieved in the AEC industry. These challenges include:

- Networking and connectivity between various sensing, communication technologies and information systems
- Fusion and analytics of heterogeneous data acquired over space and time
- Complex interaction and interdependencies between humans, environment, activities and physical and cyber infrastructure.

The MIL is a multi-purpose collaboration space that brings together industry partners, researchers and students to innovate engineering solutions. This 2-storey building features world-class facilities, including research labs, fabrication workshops and collaborative spaces. Accompanying the world-class facility is the vision to build a world-leading DT of the facility to support various building operation and research applications. The process of creating and operating the MIL-DT is expected to generate invaluable knowledge and cutting-edge technologies that will bring significant benefits to the building sector. In addition, this project explores 3 applications of DT to assess and demonstrate the benefits and impact of the DT on the operation of the MIL and the occupants and activities within. These applications include energy-efficient HVAC control, workplace health and safety, and individual thermal comfort analysis. More specifically, the objectives of this project are to:

- Enhance the existing design and deployment of a multimodal sensing network for data acquisition
- Further develop the existing data engineering and analytics platform for data communication and integration
- Add additional features to the existing domain-specific data analytics and simulation application
- Enhance the existing front-end portal for spatial visualisation and interaction with sensing data and simulation results
- Evaluate the benefits of the MIL-DT in case studies.

This report presents the current literature on DT development and details the process of designing, developing and operating the MIL-DT. The rest of this report is organised as follows: Section 2 reviews and describes the literature on DT for building operations, focusing on studies with real-world implementations. Section 3 outlines the design architecture and key functional components of MIL-DT, addressing the critical challenges in DT development and operation identified from the literature. Section 4 presents findings from 3 case studies that highlight the benefits of MIL-DT in building operations and occupant wellbeing applications. Section 5 discusses the lessons learned and proposes a design and development framework to guide future DT implementations. Finally, Section 6 provides a conclusion and sheds light on future directions in DT research and development.

2. DIGITAL TWINS FOR BUILDING OPERATION

This section reviews the current literature on creating and operating digital twins (DTs) for building operation and management applications, with an emphasis on real-world implementations. It provides a comprehensive overview of state-of-the-art and state-of-the-practice DTs within the context of the built environment. The last part of this section identifies multiple critical knowledge gaps in DT implementations.

2.1. Literature search

To obtain a comprehensive overview of the literature on DTs for building operations, the academic database Scopus was used as the primary source. The initial search targeted titles, abstracts and keywords containing "building" or "buildings," "operation" and "digital twin" or "digital twins." The 739 results were further refined by applying filters to limit the search to the engineering field and peer-reviewed journal articles. Additionally, irrelevant keywords such as "structural health monitoring", "railroads" and "aircraft" were excluded, reducing the sample size to 229 papers. A manual screening process was then conducted to exclude papers without any real-world implementation of DTs, those focusing solely on sensor accuracy without addressing building operation applications and those related to specialised infrastructure, including underground structures, power plants, airports and factories. Ultimately, 32 papers were selected for further analysis. The literature search method is illustrated in Figure 1.

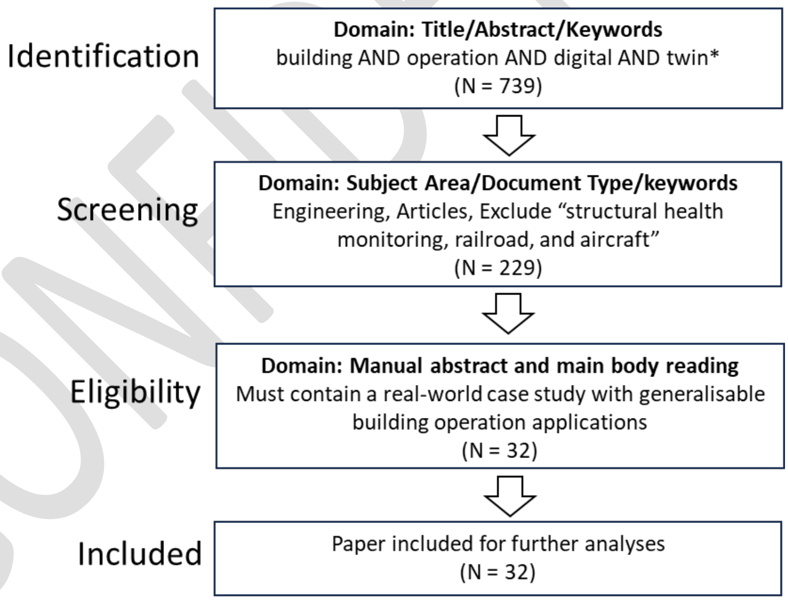

Figure 1. Literature search method

As shown in Figure 2, the identified DTs are distributed globally, with the majority located in Europe, China and the USA. These DTs were further analysed based on 4 key aspects: (1) data types and collection methods, (2) data handling, (3) targeted application and (4) DT scale and stakeholder engagement. Table 1 summarises the key features of the selected DTs with respect to these 4 aspects.

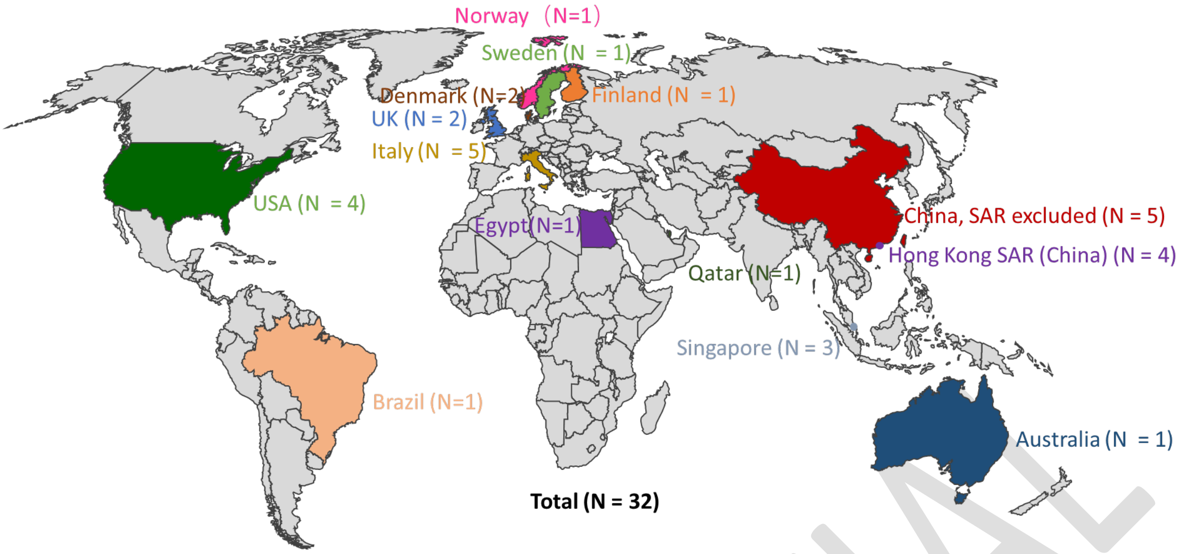

Figure 2. Global distribution of the DTs

Table 1. Summary of DTs of the indoor environment

References	Implementation scale	Data types and collection methods				Data transmitting	Data integration	Targeted application	Stakeholders engagement
		Space	Building systems	IEQ	Occupancy				
Digital twin-driven approach to improving energy efficiency of indoor lighting based on computer vision and dynamic BIM [1]	A corridor	Building geometric information (BIM model)	Lighting system layout (BIM model)	Illuminance (Camera)	Occupancy (Camera)	LAN	WebGL (Web Graphics Library)	To analyse light turn-on schedule Detect lighting system failure	Not discussed
Digital Twin of HVAC system (HVACDT) for multiobjective optimization of energy consumption and thermal comfort based on BIM framework with ANN-MOGA [2]	HVAC system	Building geometry (drawings and BIM models)	HVAC system operating status (specialised sensors)	Temperatures, pressure and airflow speed (specialised sensors)	Self-reported clothing and activities (surveys)	Not specified	Autodesk Revit	Simulate building energy consumption calculate PMV	Facility manager as DT end user
Operation optimization in large-scale heat pump systems: A scheduling framework integrating digital twin modelling, demand forecasting and MILP [3]	A heating system	N.A.	Heat pump system operating status (BMS)	N.A.	N.A.	Not specified	Microsoft Azure	Reduce heat pump operation cost considering fouling and variable electricity prices	Not discussed
Intelligent emergency digital twin system for monitoring building fire evacuation [4]	Multiple egress components (e.g., staircase)	Building geometric information (AutoCAD)	N.A.	N.A.	Number, distribution and passing time of evacuees (camera)	LAN-based wireless connectivity	Cloud server	Real-time evacuation monitoring	Not discussed
A digital twin architecture for real-time and offline high granularity analysis in smart buildings [5]	A single room	Building geometric information (measurement)	HVAC operation and lighting system layout (electro-mechanical plan drawings) Electricity usage (smart meters)	Temperature, humidity, CO_2, VOC, PMs	Number of regular occupants (Observation)	WIFI	ThingSpeak	Support Energy Plus simulation Examine energy usage with different energy storage equipment	Facility manager as DT end user
Towards democratization of digital twins: Design principles for transformation into a human-building interface [6]	A single room	Building geometric information and Zoning (observation)	N.A.	Temperature, humidity, illuminance, air flow speed	Occupant demographics, occupants' current experiences with environmental controls and desired methods to interact with a DT system (Survey and co-design workshop)	Not specified	N.A.	To explore the occupants interested DT functions and interactive DT interface	Occupant participating DT design and validation

Digital twin-enabled built environment sensing and monitoring through semantic enrichment of BIM with SensorML [7]	A single room	Building geometric information (BIM model)	N.A.	Humidity, temperature, PM2.5, NO and NO_2 (DHT-20, MP503 and PPD42NS sensor)	Number of occupants (PIR sensor)	WIFI	Cloud server	IEQ parameters monitoring	Facility manager as DT end user
An ontology-based innovative energy modeling framework for scalable and adaptable building digital twins [8]	A room	Building geometry	HVAC system operating status	CO_2	N.A.	Not specified	IFC model	Provide standard data integration for fault detection, operational optimization, and heating/cooling strategy planning	Not discussed
Building artificial-intelligence digital fire (AID-Fire) system: a real-scale demonstration [9]	A fire test room	Building geometric information (AutoCAD drawings)	N.A.	Temperature and smoke (temperature and smoke detector) Flame (Camera)	N.A.	WIFI	Cloud server	To identify critical fire events (e.g., fire development, spread and movement)	Not discussed
A tool-based system architecture for a digital twin: a case study in a healthcare facility [10]	A hospital operating room	Building geometric information (BIM model)	N.A.	Temperature and humidity (DHT11) NO and NO_2 (MQ-135) Particulate contamination (PMSA003I)	N.A.	REST API/ HTTPs (Raspberry Pi 4)	Microsoft Azure and Power BI	IEQ parameters monitoring	Facility manager as DT end user
A BIM-enabled digital twin framework for real-time indoor environment monitoring and visualization by integrating autonomous robotics, LiDAR-based 3D mobile mapping, IoT sensing and indoor positioning technologies [11]	Two rooms	Building geometric information (BIM model, 360 panorama and laser scanning)	N.A.	CO, CO_2, NO_2, PM2.5 (MQ7 CO Gas Sensor, MQ135 CO_2 Sensor, MICS-6814 NO_2 Sensor and GP2Y1010AU0F PM2.5 Sensor)	N.A.	LAN-based HTTP web server	Autodesk Revit	IEQ parameters monitoring	Facility manager as DT end user
Digital twins for decoding human-building interaction in multi-domain test-rooms for environmental comfort and energy saving via graph representation [12]	Multiple thermal test rooms	Building geometric information (BIM model)	N.A.	Floor/roof/wall temperature, heat flux (platinum resistance thermometer PT100, heat flow meter) Air velocity, temperature, relative humidity, net/mean radiation (anemometer and thermal-hygrometer, radiometer) CO_2 and illuminance	EDA signals, heart rates, perimetral skin temperature and EEG; Perceived RGB and IR spectrum (Wearable physiological and visual sensors) Subjective thermal/visual comfort (Survey)	Wired network	Neo4J database	To establish a thermal comfort database	Not discussed

				(CO_2 sensor and luxmeter)					
Digital twin for indoor condition monitoring in living labs: University library case study [13]	Multiple study room in a library	Building geometric information (BIM model)	N.A.	Temperature Humidity Illuminance CO_2 and TVOC (LoRa sensors, e.g., Mile sight IoT sensors AM107 and AM307)	Motion detection (PIR sensor in Milesight IoT sensors AM107)	Lora WAN	Autodesk Revit	IEQ parameters monitoring	Facility manager and students as DT end users
From Building Information Model to Digital Twin: A Framework for Building Thermal Comfort Monitoring, Visualizing and Assessment [14]	Multiple rooms in an office building	Building geometry (BIM models)	HVAC system layout (BIM models)	Temperature and humidity (microclimatic station produced by Tecno El with the GRILLO data logger)	N.A.	Wired network	Autodesk Revit	Calculating PMV	Interview facility manager s to determine the optimal sensor deploy strategy
Digital twin for safety and security: perspectives on building lifecycle [15]	A grain drying facility	Building geometric information (Blender software)	N.A.	Flame radiation (radiation sensor) Thermal image (thermal imaging camera)	Human' presence (motion detector)	REST API/ HTTPs (Raspberry Pi 4)	Microsoft Azure and Unity 3D	Fire detection and alarm	Facility manager as DT end user
A framework for an indoor safety management system based on digital twin [16]	A stadium	Building geometric and material information (BIM model)	Door/window operating status (Proximity sensor)	temperature oxygen concentration carbon-monoxide concentration smoke (LoRa Sensor)	Number and location of occupants (camera)	Lora WAN	Cloud server	Identify Illegal Invasion, overcrowding and fire and their locations	Safety management staff as DT end user
Showcasing a digital twin for higher educational buildings: developing the concept toward human centricity [17]	Entire building	Building geometric information (laser scanning)	HVAC operation status (BMS)	Temperature Noise CO_2	Occupants' number (people counter)	Not specified	Microsoft Azure	Energy-saving HVAC operation IEQ parameters monitoring	Facility manager and occupant participating DT design and validation
IoT open-source architecture for the maintenance of building facilities [18]	Entire building	Building geometric information (BIM model)	HVAC system operating status (IoT sensors)	Ambient temperature, humidity and illuminance (ESP8266 sensor board)	N.A.	Wired network and WIFI/MQTT (Raspberry Pi 3B)	Autodesk Platform Service (Forge)	HVAC anomaly detection IEQ monitoring	Not discussed
Modelling indoor thermal comfort in buildings using digital twin and machine learning [19]	Entire building	Building geometric information (laser scanning and BIM model)	HVAC operation status (i.e., air conditioner (remote controllers)	Temperature and humidity (DHT11, DHT22) illuminance (Light Dependent Resistor (LDR))	N.A.	WiFi and HTTP enabled wireless sensor network (WSN)	Autodesk Web Service	Calculating PMV	Facility manager as DT end user
Development of a BIM and IoT-Based Smart Lighting Maintenance System Prototype for Universities' FM Sector [20]	Entire building	Building geometric information (BIM)	N.A.	Illuminance (Lighting Dependent Resistor, LDR)	N.A.	Not specified	Autodesk Revit	Anomaly detection and maintenance scheduling	Facility manager as DT end user

Development of a Cognitive Digital Twin for Building Management and Operations [21]	Entire building	Building geometric information (BIM model)	HVAC system operating status (Building Automation System, BAS)	Temperature and CO_2	Satisfactory to acoustic, function, indoor air quality/odour, thermal, or visual comfort (occupants self-report)	HTTPS	AWS cloud	Fault detection and repair/maintenance order analysis	Facility manager as DT end user
Enhancing Space Management through Digital Twin: A Case Study of the Lazio Region Headquarters [22]	Entire office building	Geometric information (BIM model)	Energy consumption (energy sensor)	Temperature and brightness (Shelly Motion 2)	Occupants presence (Shelly Motion 2)	HTTP-enabled wireless sensor network (WSN)	PowerBI	Monitoring CO2, energy consumption and space occupancy	Facility manager as DT end user
Empowering smart cities with digital twins of buildings: Applications and implementation considerations of data-driven energy modelling in building management [23]	Entire education building	N.A.	HVAC operating status (BMS)	CO_2, humidity and temperature	N.A.	Not specified	Web-page visualisation model	Energy consumption prediction and HVAC anomaly detection	Facility managers and engineers participating in planning and validation phase
Thermal performance improvement for residential heritage building preservation based on digital twins [24]	Entire heritage building	Building geometric information (2D drawings) Material information (observation)	HVAC operation status (BMS)	Thermal image (thermal imaging camera)	N.A.	Manually transmitted (e.g., USB)	Autodesk Revit	Computational fluid dynamics (CDF) simulation	Not discussed
Multi-indicator adaptive HVAC control system for low-energy indoor air quality management of heritage building preservation [25]	Entire heritage building	Building geometric information (BIM model)	N.A.	temperature, humidity, CO_2, SO_2 and NO_2	N.A.	Wired network	A JAVA platform	To identify excessive pollutants for HVAC operation	Not discussed
Intelligent control of building fire protection system using digital twins and semantic web technologies [26]	A 4-storey school library	Building geometric information (BIM model)	Fire Device Information (Fire Protection System)	Temperature and smoke (heat and smoke sensors)	Number of occupants (Camera)	Not specified	A Java platform	To monitor building fire protection system operation	Not discussed
Intelligent monitoring platform and application for building energy using information based on digital twin [27]	Multi-levels of a high-rise building	Geometric information (3dMax)	Door/window/curtain status (automation system) Energy consumption (smart meter)	Illumination, temperature, humidity, CO_2, PM2.5 and TVOC (Zigbee sensors)	Occupant location (UWB)	Zigbee and UWB	Unity 3D	Energy-saving HVAC operation	Not discussed
Digital twin–based health care facilities management [28]	A healthcare facility	Building geometric information	HVAC operation status (BMS)	temperature, humidity, CO_2, radio frequency	N.A.	Combined WLAN, WPAN,	Unity 3D	IEQ parameters monitoring	Health care facility managers,

		(BIM model)		interference and Light (ONSET MX1102A/MX1104 sensor)		wireless USB, Bluetooth, ZigBee, WAN, WiMAX		Asset (pulsed light) maintenance	clinical engineers and DT experts co-design
Carbon emissions accounting and estimation of carbon reduction potential in the operation phase of residential areas based on digital twin [29]	A residential area	Building geometric information (BIM model) Vegetation areas (remote sensing image)	N.A.	N.A.	Transportation/vehicles (remote sensing image)	Manually transmitted	gbXML/DesignBuilder	Carbon emission estimating in building operation	Not discussed
Federated Data Modeling for Built Environment Digital Twins [30]	A campus	Building geometry (drawings and BIM models)	HVAC operation status (BMS) Maintenance records (BMS)	Temperature, humidity, CO_2 and illuminance (Radio frequency and LoraWAN sensors)	N.A.	RF and HTTP-enabled wireless sensor network (WSN) and QR code–based asset management network	Bently Systems Assetwise and Amazon Web Service	Standardise the data integration for HVAC control and IEQ monitoring	Asset manager co-create the information requirements for DT
Toward cognitive digital twins using a BIM-GIS asset management system for a diffused university [31]	A campus	Building and outdoor space geometry (BIM and GIS)	N.A.	N.A.	N.A.	Manually transmitted	PowerBI	Fire evacuation simulation	Facility manager as DT end user
Developing a digital twin at building and city levels: case study of west Cambridge campus [32]	A campus	Building geometric information (BIM model)	HVAC operating status and energy consumption (BMS)	temperature and humidity (Monnit wireless sensors)	Occupancy (Monnit wireless sensors)	RF and HTTP-enabled wireless sensor network (WSN) and QR code–based asset management network	Bentley Systems and Amazon Web Service	To forecast energy demand, detect pump anomaly, optimise asset maintenance sequence IEQ monitoring	Modelling company, university facility manager, consulting company, Researchers Participating DT design and validation

2.2. Data types and collection methods

The majority of the 32 DTs identified focuses on the indoor environmental quality (IEQ) parameters and their relationship with building geometric data (e.g., topology of building and rooms, location of furniture). IEQ parameters refer to numerous factors within a building affecting occupants' health, comfort and activity productivity [33]. These factors include indoor air quality parameters, such as temperature, humidity, pollutants (e.g., CO_2 concentration, PM2.5, NOx) [11, 13, 25, 28], illuminance [27], noise [17], radio frequency interference and fire-related parameters (oxygen concentration, CO concentration, smoke and flame) [15, 26]. Acquiring this wide range of data requires various specialised and connected sensors, installed either on fixed locations [13, 15] or mobile platforms [11]. In addition, some DTs utilise cameras and computer vision (CV) techniques to identify objects of interest (e.g., flames) and image illuminance [1, 4, 26].

Building geometric data, another type of data essential to DT applications, is often provided by BIM models. BIM models, which are sometimes reinforced by reality capture technologies such as laser scanning and 360 panorama cameras to enrich the BIM model with real-time changes, usually serve as the foundation of data mapping (e.g., by area) and visualisation in such DTs [12, 32]. Known for their semantic richness, BIM models also supply additional information to the DT, such as materials [24], manufacturers [16], HVAC system layout [32] and lighting systems [16]. Alternative sources of building geometric data, such as manual surveying results [24], 3dMax [27] and AutoCAD drawings [4], have been utilised, depending on the scale of the building and availability of BIM models. With newly built and technology-equipped buildings, real-time status of HVAC systems, doors and windows and lighting systems could be streamed from the Building Management Systems (BMS) to a centralised database [32].

As the primary users of indoor spaces, occupants' behaviours significantly impact building operations and are, in turn, influenced by these environments. Given the diverse nature of occupant behaviour, an accurate definition of data requirements according to the needs of building management is critical. The most common data types include tracking the presence and number of occupants in specific areas, such as lecture theatres, using Passive Infrared (PIR) technologies installed at entrances and exits [1, 5, 24, 26, 32]. This information enables asset managers to understand and respond to fluctuations in IEQ parameters, facilitating proactive adjustments to HVAC systems. In larger spaces, such as workshops, the distribution of occupants becomes important, requiring precise location data. Advanced technologies such as CV and ultra-wideband (UWB) are used to gather mobility insights, including movement speeds and patterns [4, 15, 17, 27]. In addition, data concerning occupants' thermal sensation and physiological signals (e.g., heart rates) could be collected through more intrusive methods, such as surveys and smartwatches, generating precise information about occupants' comfort and wellbeing and serve as benchmarks for data interpretation, particularly for customising HVAC settings preferences [6, 12]. Figure 3 summarises the data types and collection methods, with the inner circle representing data classes, the middle circle representing data types and the outer circle showing sensor/data sources.

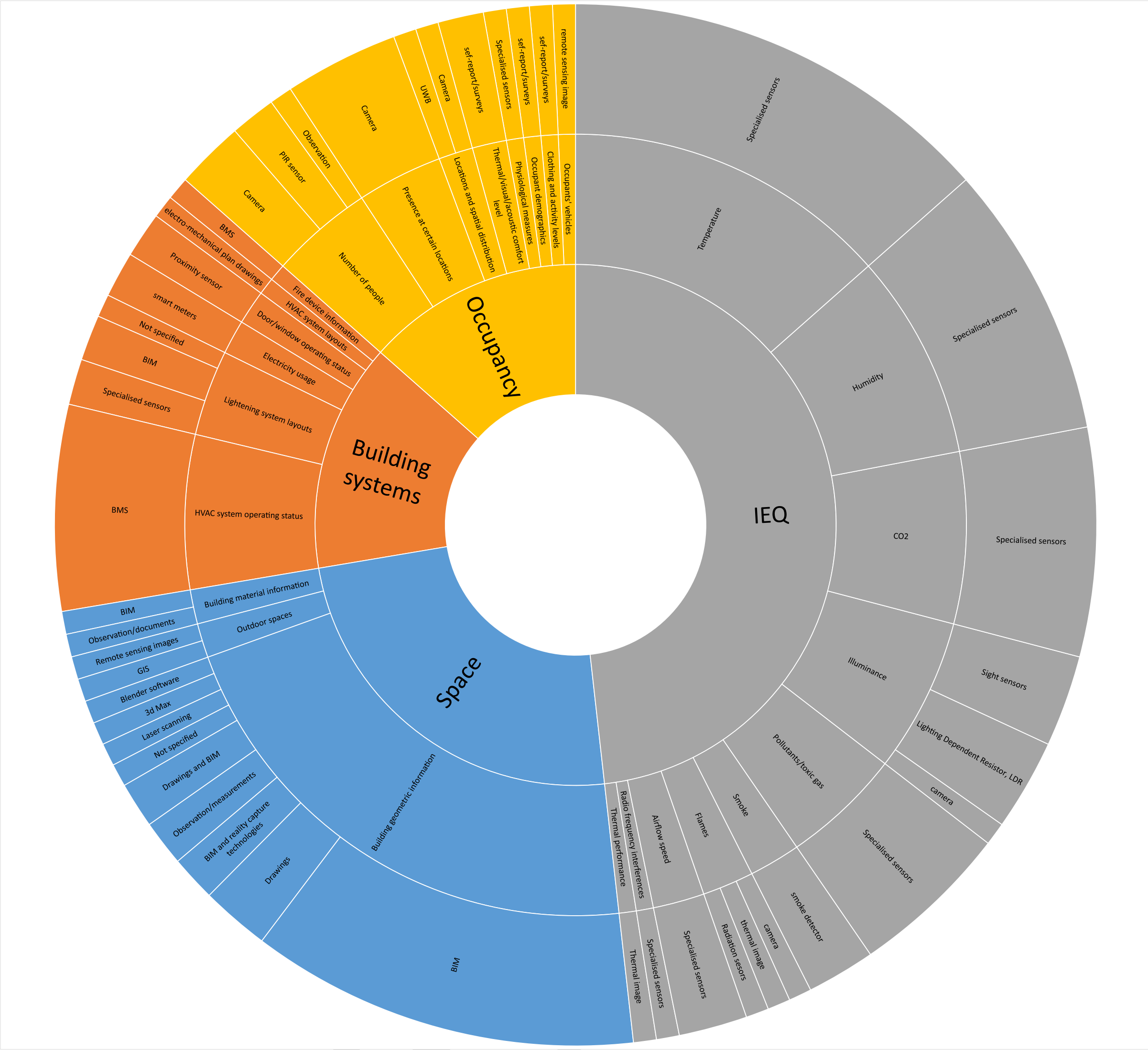

Figure 3. Data types and corresponding collection methods

2.3. Data handling

Data handling in DTs involves 2 main stages: the first stage encompasses the transmission of data from individual sensors to a centralised database and the second involves synchronising and fusing data from various sources. In the first stage, Wi-Fi [25] and cellular connection [28] are predominantly used due to their high data rate capabilities and widespread installation in indoor environments. These 2 technologies are particularly useful in healthcare facility management and intelligent building operations, where high-speed data transmission is critical for real-time monitoring and control [28]. Long range wide area network (LoRaWAN) protocol is also utilised for their long-range and low-power features in university campus DTs independent of central internet services [13]. The integration of (message queuing telemetry transport) MQTT in data transmitting underscores its growing importance in Internet of Things (IoT) ecosystems, supporting complex networks of sensors that require reliable and efficient data exchange. MQTT also plays a crucial role in supporting edge computing, which has been increasingly adopted to enable DT scalability, efficient analysis and, potentially, real-time responses [18].

Once IoT data is transmitted to a centralised database, data fusion occurs. For smaller-scale DTs that do not handle large volumes of data or require low latency, using a BIM model for data integration and visualisation is an intuitive approach [11, 13, 24]. However, BIM software typically has a limited capacity to manage real-time data. An effective alternative is to utilise cloud service platforms such as Microsoft Azure IoT Hub [10, 15, 17, 32] and Amazon Web Services [32].

Databases hosted on these platforms, such as MySQL [18, 25] and Neo4J [12] can be queried for further data analysis. In this setup, BIM models are uploaded to the cloud and interconnected with IoT data to provide spatial context. Figure 4 summarises the platform used for data handling tasks in the reviewed literature.

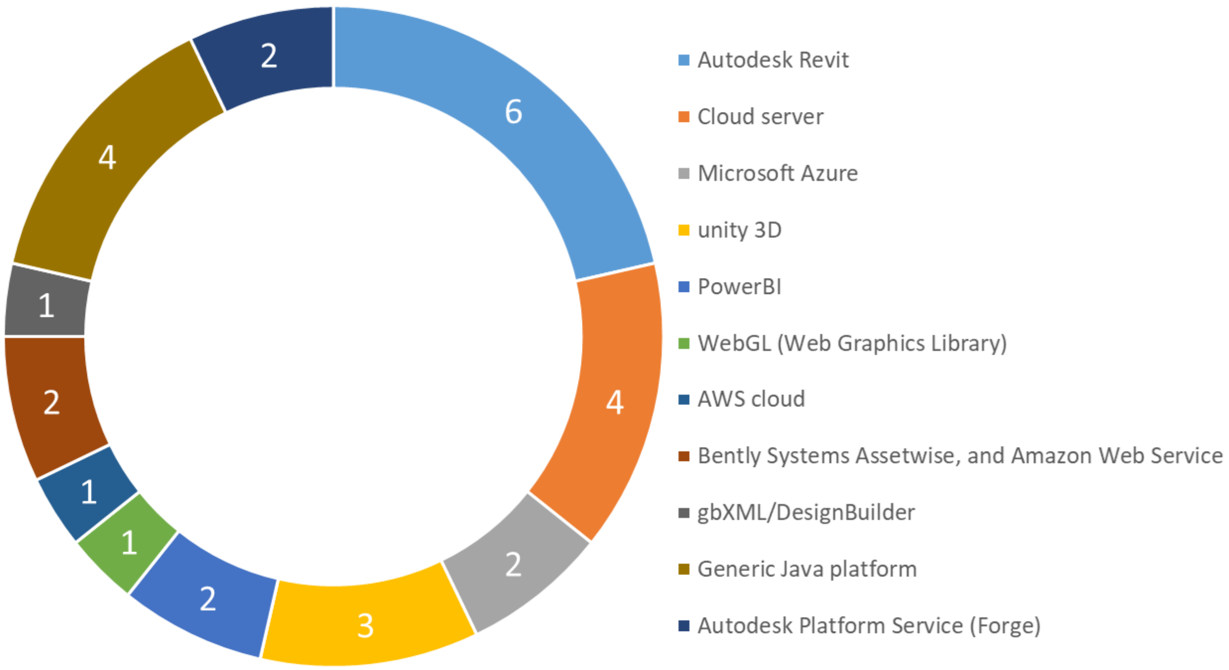

Figure 4. Software and cloud services used in DTs identified in the literature

2.4. Target applications

The integrated database serves as the foundation for further data visualisation and analysis. Commonly, this involves the visualisation of IEQ parameters [10], which are integrated into further analyses such as Computational Fluid Dynamics (CFD) simulations [24, 25]. These simulations are essential for predicting the dispersion of toxic air and for conducting building energy simulations (e.g., Energy Plus) [27]. In these analyses, building information and real-time IEQ parameters are input into simulators, wherein the behaviour of HVAC systems is assumed to be static and stable. In reality, however, HVAC systems' status (e.g., real-time air pressures and anomalies) are of significant interest to asset managers. Consequently, DTs have been utilised for these monitoring purposes and, based on the frequency of their use, to prioritise maintenance [32]. Similarly, lighting systems are also a focal area, where DTs have been proposed to monitor illuminance, optimise lighting schedules [1] and, in special cases such as healthcare facilities, monitor the decline and anomaly of pulsed lights [28].

While these DTs monitor ambient conditions of indoor environments or specific building systems, DTs are also quite useful in analysing extreme events. Critical fire event identification, including the development, spread and movement of fire, is a vital aspect, which usually leverages CV and temperature or smoke sensors to proactively identify fires [9, 26]. Some DTs extend their focus from fire events to additional security applications, such as detecting unauthorised entries and overcrowding in public areas, facilitating effective and timely responses [1]. Figure 5 illustrates the targeted applications and their respective frequencies of the reviewed DTs.

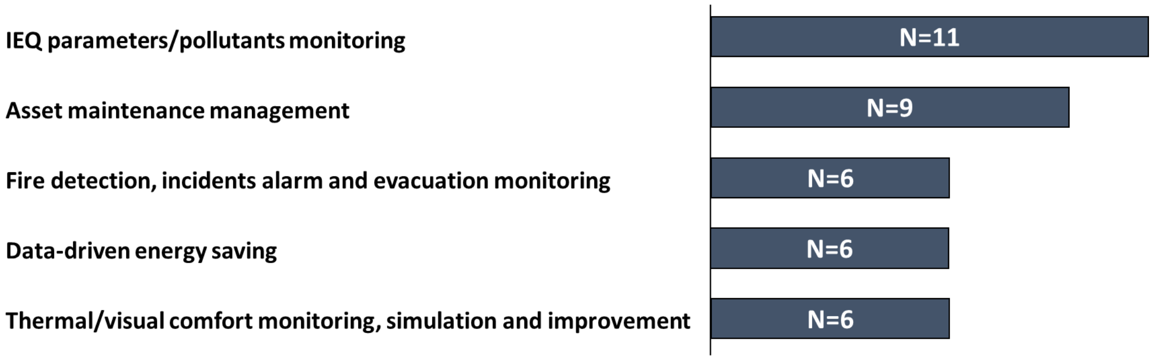

Figure 5. Targeted Applications of the DTs

2.5. DT scale and stakeholder engagement

DTs of indoor environments operate at various scales, ranging from specific egress components (e.g., staircases) [1], individual and multiple rooms [5, 9-13] to entire buildings [15, 16, 26-28] and even university campus-wide systems [32]. The scale of application highlights the versatility of DTs to meet diverse stakeholder data requirements. Figure 6 illustrates the scales of reviewed DTs. It has been observed that complex buildings, with multiple spaces with varied functions, typically involve more stakeholders [32]. However, even at the same scale, methods of stakeholder engagement differ. Stakeholder engagement with DTs predominantly occurs at the final stage, where facility managers, occupants and specialised staff such as librarians or clinical engineers merely view the outputs of the DT system [5, 7, 10, 11, 13, 15, 16]. In this capacity, DTs serve primarily as decision-support tools, providing insights and analytics that inform stakeholders' operational, safety, or management responsibilities.

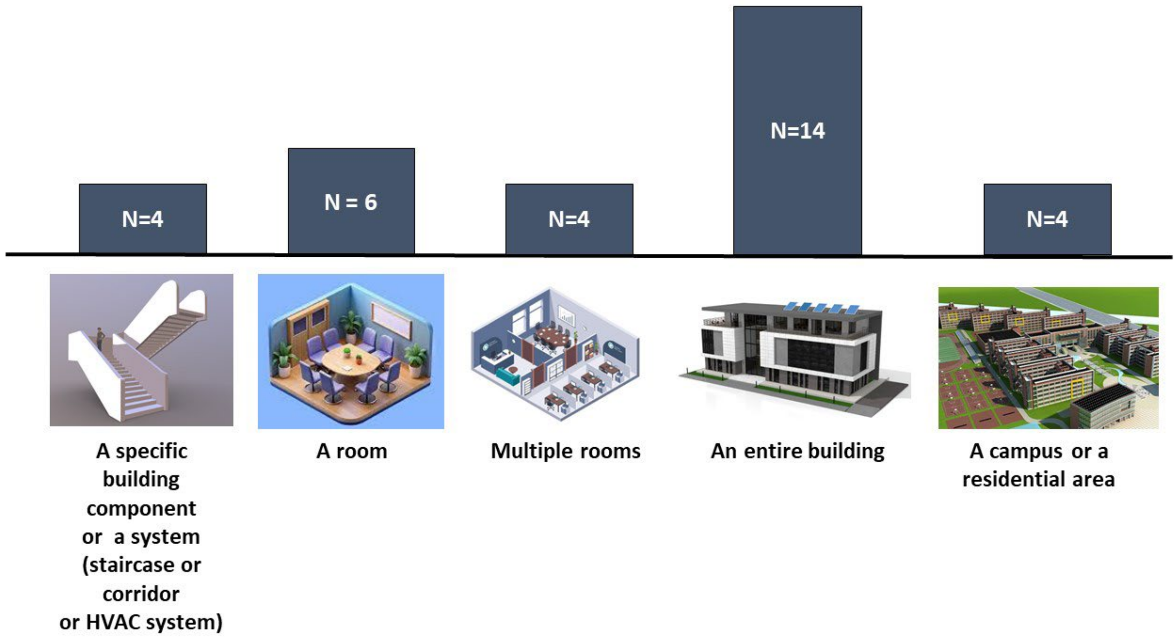

Figure 6. Scales of the DTs

Significant involvement has also been observed at the design and validation stages, especially in complex settings such as healthcare facilities and university campuses [12, 17, 28, 32]. This level of engagement reflects a collaborative approach to DT development, where contributions from various stakeholders are crucial for shaping the DT's architecture and ensuring its accurate representation of the physical asset and its dynamics [34]. Nevertheless, compared to the norm in DT development, such in-depth engagement in the development of DTs remains rare. This phenomenon could be a result of development modes. Most DT developments are led by researchers in a short-term research project and, due to the limited resources available, these DTs are primarily technology driven [13]. Thus, such development tends to be influenced by researchers' understanding and the sufficiency of available technologies and data handling methods. In contrast, external development, which leverages the resources of commercial modelling/data companies, usually engage more stakeholders in the development [32]. This approach is feature-focused with great technology proficiency, but the complexity of development coordination could limit continuous yet incremental adaptation (e.g., trial-and-error analyses for research purpose). Therefore, a DT development methodology is required, which is not bottlenecked by limited by technology capacity and supports addressing continuous feedback in the long term. Table 2 summarised the engaged stakeholders and the engagement method throughout the lifecycle of reviewed DTs. It is worth noting that 37.5% of the papers introduce their DTs without discussing the stakeholders.

Table 2. Engaged stakeholders and engagement methods in the DTs

	Facility managers	Occupants	Engineers and researchers	Safety managers
Engaged in design	2	0	0	0
Engaged in development and validation	5	1	4	0
Engaged as end-users	11	1	0	1

2.6. Knowledge gap and practical challenges

Real-time, multi-modal data handling

Many methods, particularly those designed for small-scale indoor environments, rely on Building Information Modelling (BIM) software, such as Autodesk Revit, as a data handling platform. While BIM offers intuitive visualisation and detailed architectural representations, it has limited capabilities for handling real-time data. This limitation poses significant challenges for applications that require up-to-the-minute information to make informed decisions.

Even platforms that are equipped with real-time data capabilities often struggle to manage the complexity and volume of data from diverse sources. This includes data from sensors, IoT devices and other building systems, which can vary widely in format and frequency. The inability to efficiently integrate and process this heterogeneous data hinders the scalability of these platforms, making it difficult to apply them to larger or more complex environments.

To overcome these challenges, there is a need for more advanced data handling solutions that can seamlessly integrate real-time data from multiple sources. This could involve the development of middleware that standardises data formats and protocols, enabling smoother data exchange and integration. Additionally, leveraging cloud computing and edge computing technologies can enhance the processing power and storage capacity needed to handle large-scale data in real-time.

Further, incorporating machine learning and artificial intelligence can improve the ability to analyse and interpret complex data sets, providing actionable insights and predictive analytics. These technologies can help identify patterns and trends that might not be apparent through traditional data analysis methods, thereby enhancing the overall functionality and scalability of BIM platforms.

Occupant behaviour capture and modelling

Tracking occupant presence and behaviour is critical for optimising building operations. However, methods for accurately and non-invasively capturing this data, such as mobility patterns and physiological signals, remain underdeveloped and largely unexplored. Current DTs often lack advanced interpretation capabilities that can provide deeper insights into occupants' behaviour, including their actions, clothing and interactions with their surroundings.

To address these gaps, it is essential to develop and integrate sophisticated sensors and data analytics tools that can capture and interpret a wide range of occupant behaviours. For instance, advanced computer vision techniques could be used to analyse video feeds, identifying specific actions and interactions within the space.

Further, understanding the context of occupant behaviour, such as the influence of environmental factors (e.g., lighting, temperature) and social interactions, can significantly enhance the accuracy and usefulness of the data collected. By incorporating machine learning algorithms, DTs can learn from historical data to predict future behaviours and adjust building systems proactively to improve comfort, safety and energy efficiency.

Stakeholder engagement and feedback

Most DT developments are primarily technology-driven, with minimal involvement of stakeholders during the design and development phases. This approach often results in solutions that do not fully address the practical needs and challenges faced by end-users. To ensure that DTs effectively meet real-world requirements, increased collaboration between researchers and end-users is essential. Engaging stakeholders early and throughout the development process can provide valuable insights and feedback, leading to more user-centric and practical solutions.

However, many DT developments are driven by short-term research projects with limited resources. These projects often focus on immediate technological advancements rather than long-term sustainability and future-proofing. As a result, the solutions developed may not be robust enough to adapt to evolving needs and technological changes over time.

Additionally, the lack of continuous feedback mechanisms between stakeholders and DT systems further exacerbates this issue. Without regular input from end-users, there are fewer opportunities for iterative improvements and refinements. Continuous feedback is crucial for identifying and addressing emerging issues, enhancing system performance and ensuring that the DT remains relevant and effective in the long run.

Privacy and ethics protocols

The way many DTs capture personal data often lacks adequate privacy safeguards. Without clear anonymisation protocols or ethical guidelines on data ownership and consent, there is a significant risk of privacy breaches and misuse of personal data. This oversight can lead to serious ethical and legal implications, undermining user trust and the overall integrity of the DT system.

Although privacy-preserving methods in the IoT and CV exist, they are rarely considered in current DT implementations. These methods include techniques such as data anonymisation, encryption and secure data storage, which can significantly enhance the privacy and security of occupant data. However, their integration into DT systems remains limited, often due to a lack of awareness or prioritisation of privacy concerns during the development process.

3. MONASH INNOVATION LABS DIGITAL TWIN (MIL-DT)

This section introduces the design and development of an end-to-end DT for a multi-purpose facility, the MIL. It will continue to present the implementation of the DT architecture and the realisation of key functional components.

3.1. Monash Innovation Labs (MIL)

Located at Monash University's Clayton campus, the MIL is a recently retrofitted multi-storey facility that features cutting-edge laboratories, workshops, modern offices and collaborative spaces (Figures 7 and 8). This facility provides businesses with the spaces and infrastructure to design, test and develop new innovations and collaborate with researchers and students across various STEM fields. Since the conception of this facility, Monash University has been dedicated to making it a world-class facility for research and innovation, underpinned by a DT.

Figure 7. Main entrance of the Monash Innovation Labs (MIL)

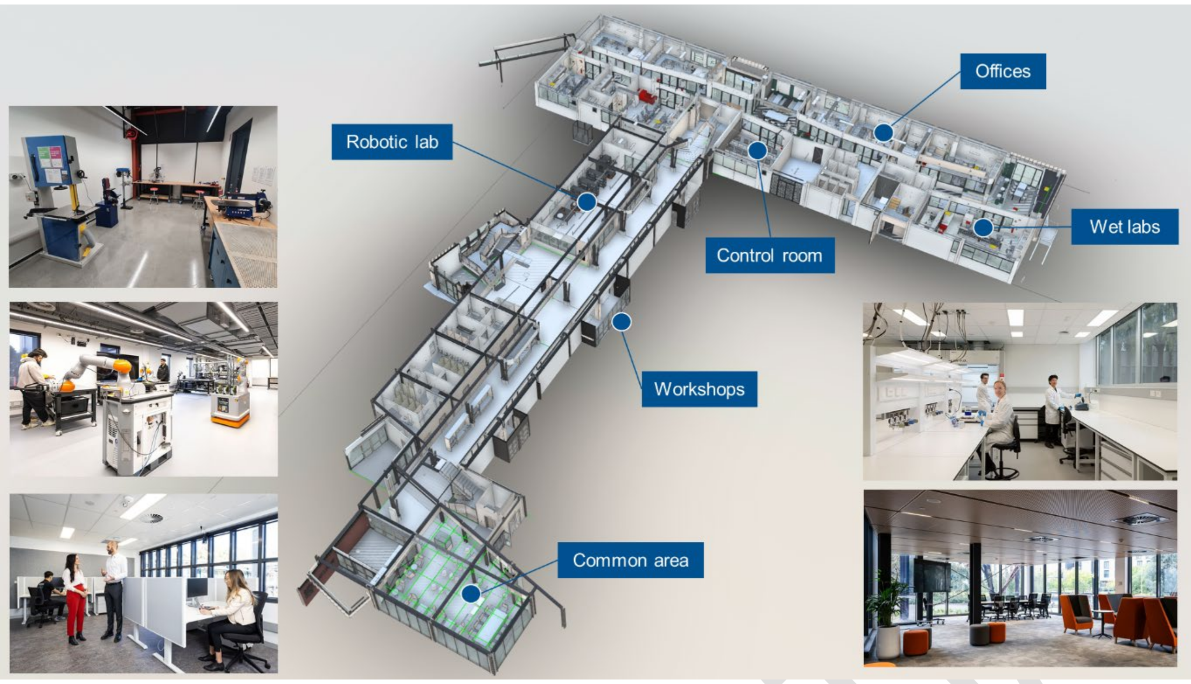

Figure 8. Ground floor and functional spaces in MIL

3.2. MIL-DT architecture

After reviewing the state-of-the-art in DT for building operations and engaging stakeholders to understand their expectations of the DT, the project team created a system architecture to describe the key functional component and their interactions in the DT. The architecture consists of 6 layers: the physical layer, data acquisition/edge computing layer, transmission layer, data-model integration layer, interoperability layer and application layer (Figure 9).

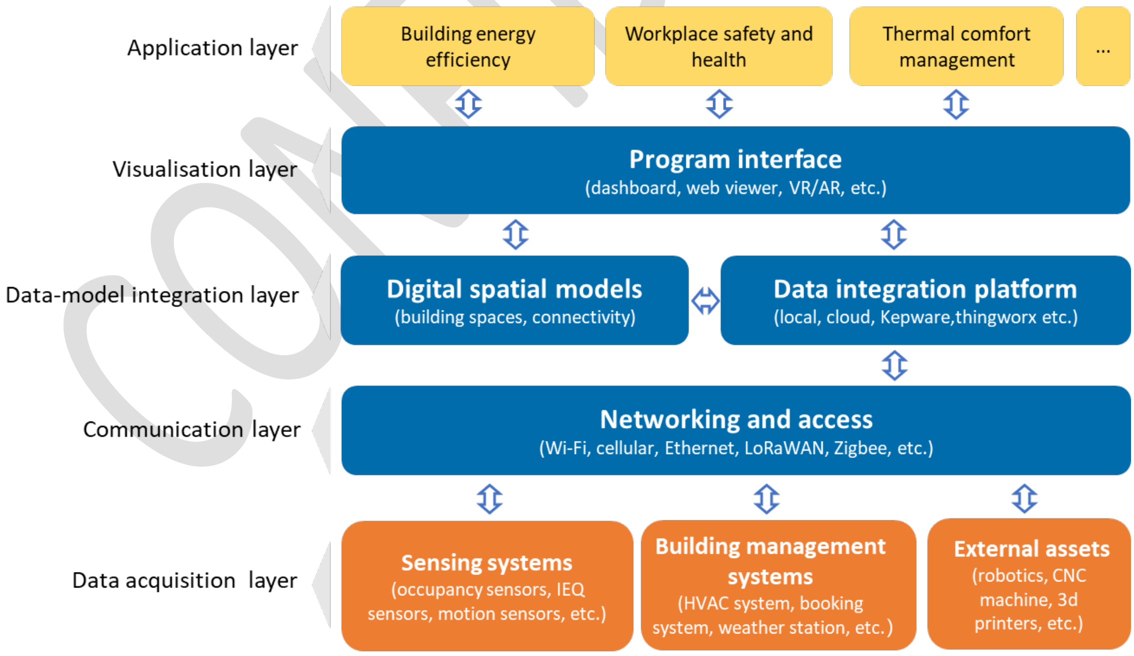

Figure 9. System architecture of MIL-DT

At the bottom, the **data acquisition layer** features 3 types of systems that collect data that represents the real-time status of physical building assets and occupants. In the sensing systems, multiple types of sensors were employed to capture space occupancy, IEQ parameters (e.g., thermal comfort and air quality) and occupant mobility and behaviour. Data concerning the operation of various building assets is acquired via APIs from building management systems, such as the HVAC operation data from the building automation system (BAS). In addition to building systems, other specialised assets, such as robotics, computer numerical control (CNC) machines and 3D printers, have to connect to the DT system to monitor their condition and performance.

In the **communication layer**, various protocols are used to transmit sensing data and operational data from other systems to the DT system, depending on the data type and requirements of these systems. They ensure seamless and robust data exchange between the physical and digital entities by minimising delay and data loss when data is streamed from the sensors to the server.

The **data-model integration layer** is responsible for creating and maintaining a high-fidelity digital model that reflects the as-built condition of the building for which the DT is created. Through this digital model, sensors in the physical layer are georeferenced according to their physical locations in the building. This data-model integration ultimately provides spatial context for sensing data, which is critical to make sense of the data and consequently leverage it in domain-specific analyses. The processed data is then synchronised and stored in a relational database hosted on a cloud server.

Moving up, the **visualisation layer** represents the building operation data together with the spatial model in different ways that suit the target applications. These visualisation interfaces may include dashboards, 3D viewers and virtual reality and augmented reality (VR/AR) on desktop or mobile devices. In addition, these interfaces need to offer visualisation and analytic functions specific to the target applications.

At the top of the architecture are the **main target applications**, which drive not only the decisions on the visualisation approach but also decisions on what types of data need to be acquired and how it should be transmitted and stored in the lower layers in this architecture. At this stage, the development and operation of the DT are driven by 3 main target applications: building energy efficiency, workplace safety and health and thermal comfort management.

3.3. MIL-DT key functional components

As-built high-fidelity digital building model

The foundation of any DT for building operation is a high-fidelity digital model that represents the as-built condition of the building being twined. The DT developed in this project utilised the architectural BIM model created by the architecture firm as the base spatial model. Since many design changes occurred during construction, the architectural BIM model does not capture them and thus needs to be updated. For this purpose, 25 laser scans were conducted using Faro Focus M70, creating an as-built representation of the facility in the form of point clouds. The registered point cloud was used as a reference to update the architectural BIM model, resulting in an as-built high-fidelity digital model. This method is illustrated in Figure 10.

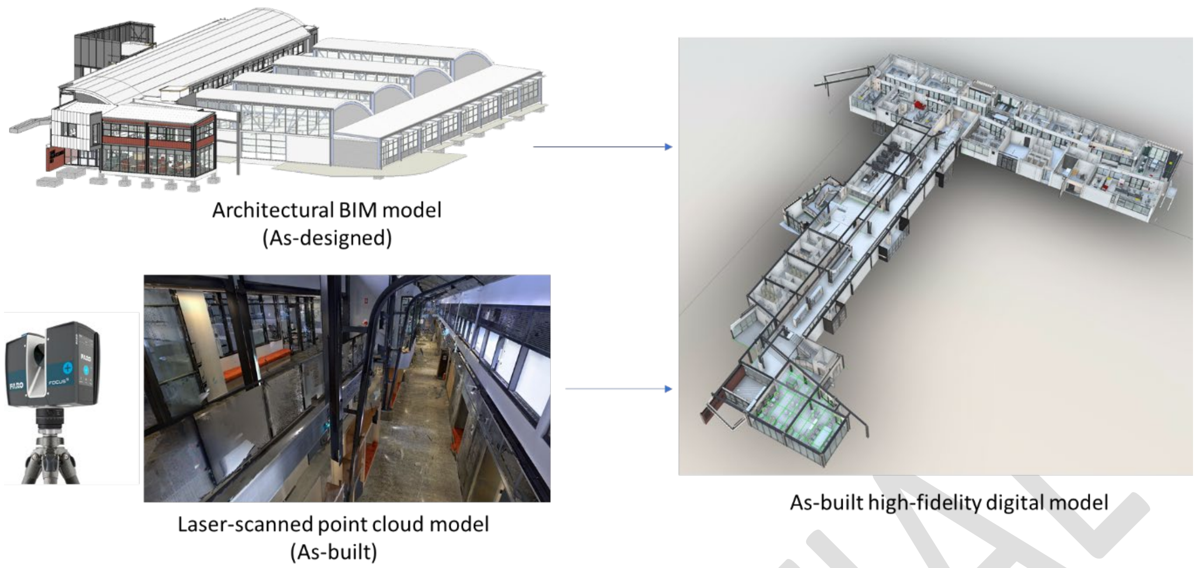

Figure 10. Creating an as-built high-fidelity digital model for the DT

Multimodal sensing network for data acquisition

Driven by the 3 target applications (i.e., building energy efficiency, workplace safety and health and thermal comfort management), we conducted a thorough review of the literature and the market to decide the types of data needed for these applications and the specific sensors suitable for acquiring data. As a result, 5 types of sensors were selected to constitute the sensing systems of the DT. They include IEQ sensors, depth cameras, LiDAR (Light Detection and Ranging) sensors and area occupancy and entry sensors. Their specifications are presented in Table 3.

Table 3. Specification of the multimodal sensing system

Sensor type	Brand & model	Cost	Quantity	Raw data acquired	Insights
IEQ sensors	Ethera Nemo	$1000	78	Air temperature, humidity, CO_2, particulate matter	Thermal comfort, air quality
Depth cameras	Intel RS D455	$419	197	Video footages	Occupant location and behaviour
LiDAR	Quanergy M8-PoE	$10900	20	3D point cloud	Object detection, scene updating
Occupancy sensor	XYsense S-A	$638	118	Space occupancy	Space utilisation
Entry sensors	XYsense S-E	$1945	76	People counting data	Foot traffic

Based on the sensing coverage and anticipated use scenarios, a detailed spatial layout of each sensor type was determined, which was then refined based on installation constraints (e.g., access, power supply) (Figure 11). The off-the-shelf IEQ sensors, the occupancy sensors and the depth cameras were mounted at different heights on the wall or on the ceiling to maximise their coverage. It is worth noting that for the depth cameras, a casing was custom-built by 3D printing to house 2 depth cameras and an edge computer (Figure 12). This configuration ensured that the viewing angle of the 2 cameras was fixed and that they could be connected to the edge computer directly.

In addition to the sensing system, we also established a one-way communication with the building automation system (BAS) to livestream HVAC operation data, such as fan speed, on-coil temperature and fresh air volume, at a frequency of 10 minutes. This data is essential in building performance and energy efficiency analyses, as demonstrated in the first case study in Section 4.

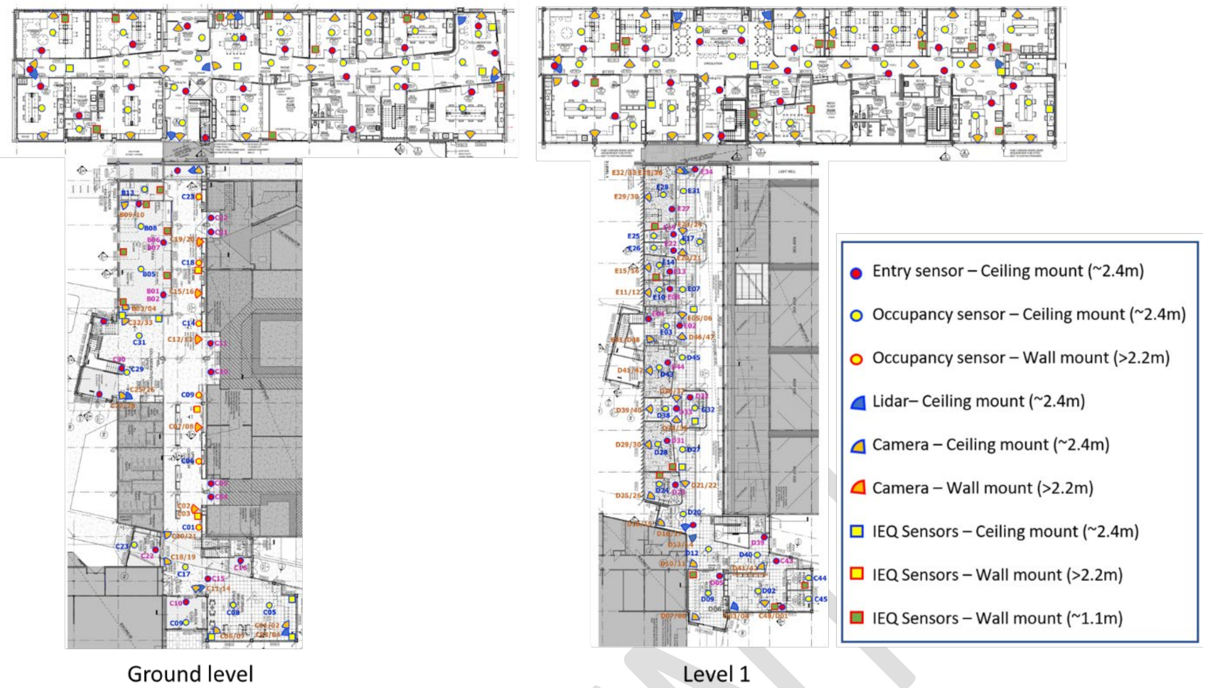

Figure 11. Installation layout of the multi-modal sensing network

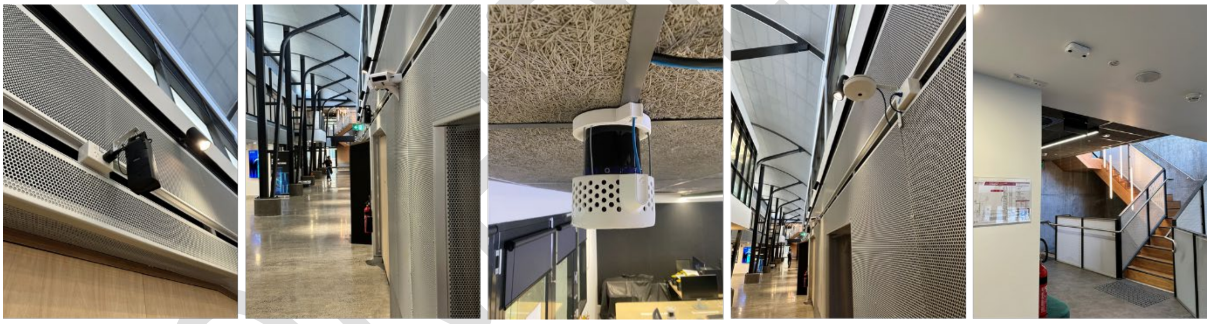

Figure 12. Deployment of 5 types of sensors in MIL. From left to right: IEQ sensors, depth cameras, LiDAR, occupancy sensor, entry sensor

Data engineering and analytics platform for data communication and integration

The MIL-DT data platform is a core component that consolidates various use cases and provides heterogeneous data in multiple formats for applications. The platform offers a range of features, including data ingestion, heterogeneous data storage and post-processing for both structured and unstructured data from IoT devices and third-party data platforms. The data platform is a vendor-neutral solution built on a cloud computing system that enables digital twin use cases by integrating IoT sensor devices to collect heterogeneous data sources. The platform performs various pre- and post-processing tasks on raw, structured and unstructured data from IoT devices. Data is accessed securely through a scalable analytical dashboard. The Data Platform supports a range of DT use cases by facilitating data ingestion, storage, processing and analysis of heterogeneous data from IoT devices and platforms. It provides an API-driven and data-access-oriented approach, allowing consumers (e.g., researchers) to work with data in both real-time and offline modes using a robust data analytics dashboard. The platform is modular, making it easily integrable with other components and frameworks for building end-to-end data pipelines.

The MIL-DT requires heterogeneous data from various IoT infrastructures and building management systems. A key challenge has been creating a unified system to provide diverse data that can be leveraged to develop an effective digital twin solution, including data from video analytics. The project demands both live and historical data from different parts of the Monash Innovation Lab building, which is accessible on demand. This requirement is met by the data platform, which delivers an end-to-end solution, from IoT device infrastructure to data storage and processing, providing a unified data stream for visualisation and dashboard creation.

This project has developed a smart infrastructure to support smart building and smart manufacturing use cases by integrating hundreds of IoT sensors with both wired and wireless connectivity throughout the building. This smart infrastructure serves as a testbed and backbone for enabling research and development projects using real-time and historical heterogeneous data.

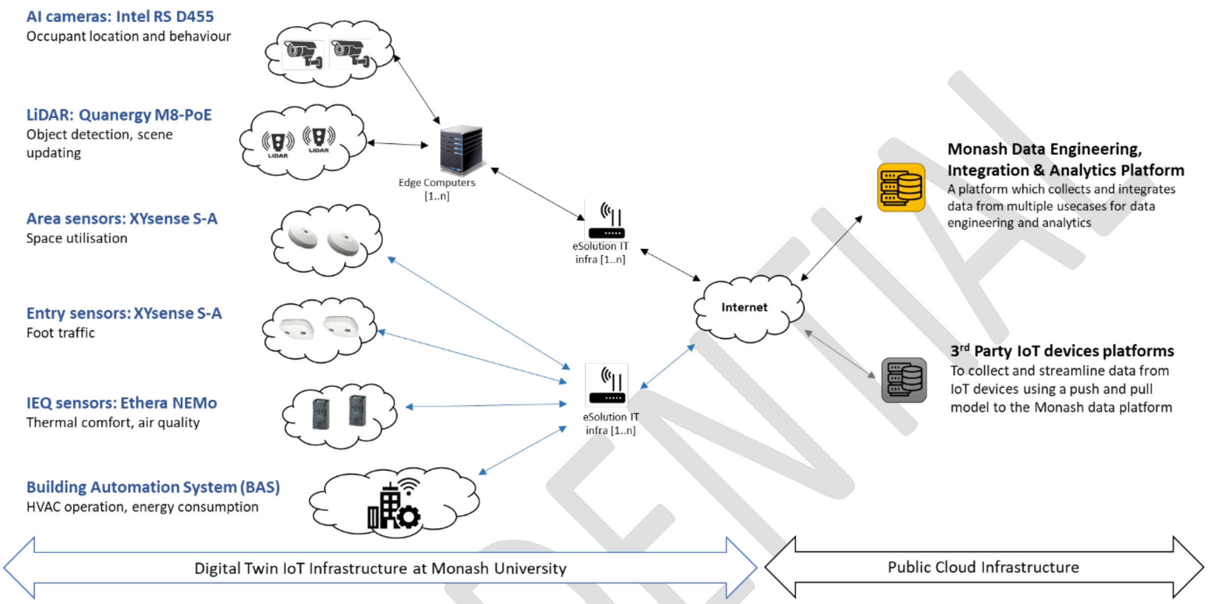

Figure 13. Deployment Architecture of MIL-DT data platform

Figure 13 illustrates the high-level deployment architecture, showcasing smart cameras, LiDAR systems, edge computing infrastructure, occupancy and people counting sensors, indoor environmental sensors and building automation sensors. The IoT devices are tightly integrated with the vendor platform, which requires additional integration efforts with the data platform. The data platform provides data engineering and integration infrastructure, enabling a unified method of data access for seamless application and service integration.

The architecture provides an end-to-end solution that integrates heterogeneous IoT device infrastructure with the data platform for data integration, pre- and post-processing, analytics and AI workloads. This solution architecture is implemented throughout the Monash Innovation Lab to deliver smart services for various use cases. The MIL-DT leverages Monash Innovation Lab's smart infrastructure to build multiple layers of applications and services to develop a digital twin solution. Figure 14 illustrates the Monash Innovation Lab's solution architecture, which consists of heterogeneous data sources through IoT infrastructure, a cloud-based data integration and engineering platform, an edge-based data platform and various applications and services.

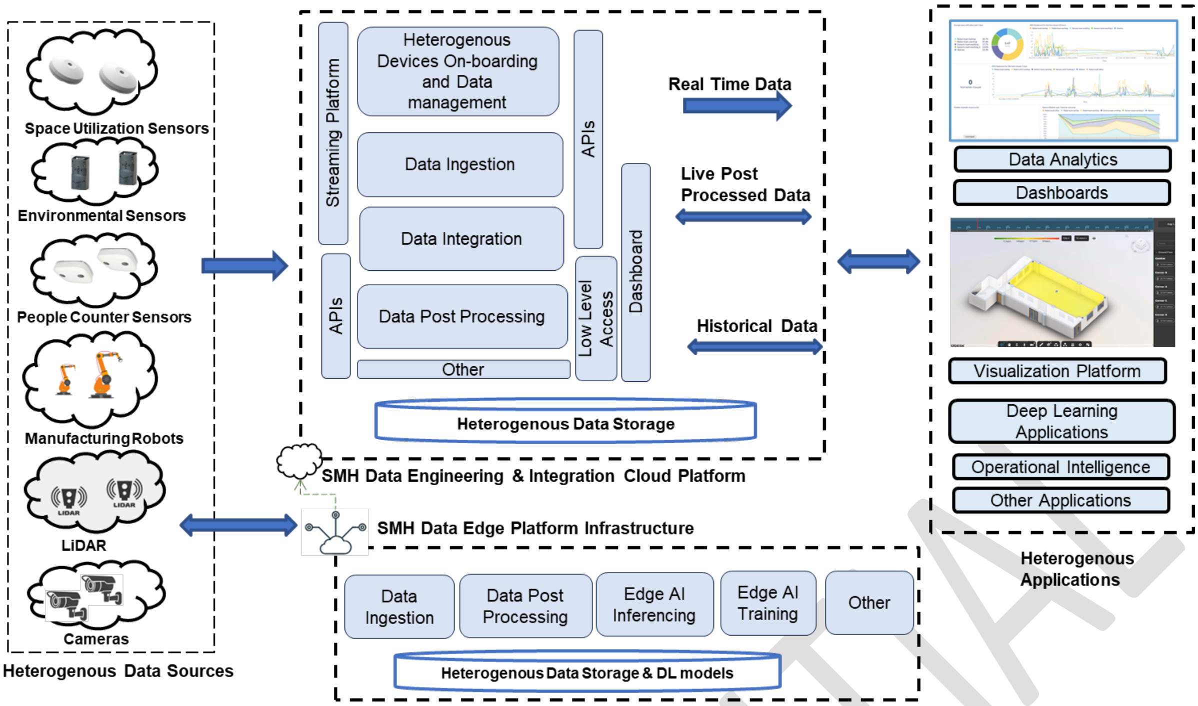

Figure 14. Solution architecture of MIL-DT data platform

The MIL-DT has incorporated hundreds of IoT devices for people occupancy monitoring, people counting, indoor environmental sensing (e.g., CO_2 levels, temperature) and smart cameras with edge computing for local AI inference. The infrastructure also includes smart manufacturing use cases with robots and 3D printers. The cloud and on-premises data platforms integrate heterogeneous IoT devices from different vendors and their platforms, providing a unified data format for accessibility and enabling diverse workloads. The cloud-based data platform is built on AWS services and offers various capabilities, including data ingestion, pre- and post-processing and multiple methods of data access via high- and low-level APIs. MIL-DT utilises low-level APIs to access and post-process data for various applications, including the Autodesk digital twin framework. Additionally, the infrastructure integrates smart cameras with an edge computing infrastructure that uses state-of-the-art AI solutions to enable a privacy-conscious people activity identification system. The MIL-DT has also expanded to include features that assess and enhance comfort levels.

Domain-specific data analytics and simulation

A visual analytics system is designed and developed to provide the MIL-DT with dynamic data regarding pedestrian mobility trajectory, pose estimation and activity identification using smart cameras, perception algorithms, deep learning algorithms and edge computing solutions. The camera system involves capturing the movement of individuals and their corresponding actions, offering valuable insights into various contexts. In addition to determining each individual's position and velocity, we perform action recognition, objection manipulation and person-to-person interaction analysis to provide a more in-depth look at human mobility. However, the utilisation of camera-based solutions raises privacy concerns and other challenges.

Our solution for the computer vision sub-system was designed to be compliant with privacy guidelines, provide real-time analysis for the immediate detection of changes, anomalies or problems and be computationally scalable with multiple cameras and people and camera-agnostic and retrofittable into existing infrastructure.

To ensure camera-agnostic compatibility, the system was designed to accommodate various camera models, provided they meet minimum hardware requirements and have image processing done on the edge device, such as a Mini-PC. The cameras used in the system have a high-resolution colour camera and depth sensing technology.

For the system to be privacy compliant, we must ensure that the raw video frames captured by the cameras are handled in a secure manner and that the information extracted from the frames doesn't include any sensitive information. To ensure that a malicious 3rd party could get access to the raw video feed, we utilise a decentralised architecture. We achieve this by having the video processing run on the edge and connecting the camera directly to the edge device via USB or Ethernet. Thus, the raw camera data is transmitted over a cable, making it impossible for the data to be intercepted. Additionally, the raw frames are discarded after the necessary image processing has been done. While the system offers a live camera view, it strictly adheres to privacy laws by employing real-time video frame processing techniques such as blurring and overlaying a skeleton figure on individuals, effectively preventing their identification.

To ensure privacy compliance, the extracted and stored data should not contain personally identifiable information. To gain variable insight regarding the individuals' movements while still being compliant, a human pose estimation machine learning algorithm was implemented to extract the skeleton of each individual within the environment. The Human Pose Estimation Machine Learning Algorithm used for the project was OpenVINO [56]. This algorithm was chosen over the other machine learning algorithms as it provided the best compatibility with the hardware we were using, scaled the best with more subjects in the frame and provided the lowest latency. The Human Pose Estimation Algorithm detects the body skeleton consisting of 19 key points in the 2D and 3D space, along with their connections, including their ears, eyes, nose, neck, shoulders, elbows, wrists, hips, knees and ankles (Figure 15).

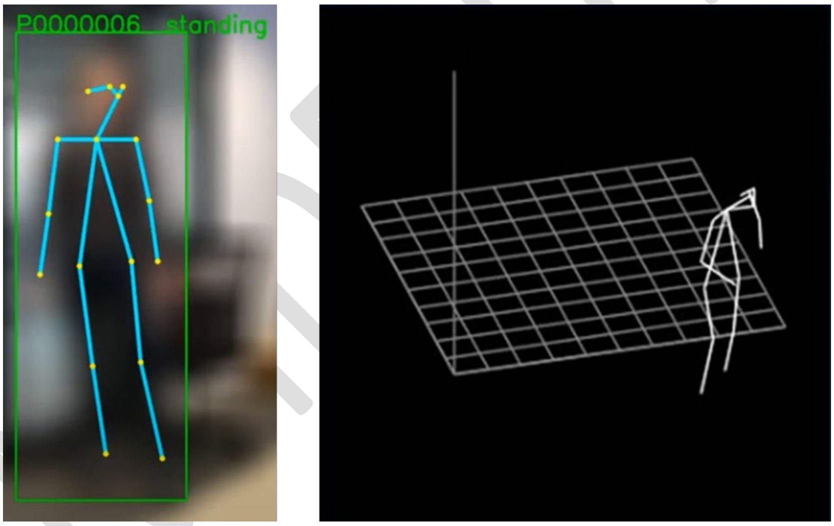

Figure 15. Action detection performed on the pose estimation of the individual which is being displaying on the privacy-compliant video feed (left), 3D visualisation of the pose estimation, highlighting the 19 key points and their interconnections (right)

Using the position of each individual given by the Pose Estimation Algorithm, we can assign a Unique Person Identification Number to each individual and compare the change in position over time to track a person through the environment. This person identification number is a randomly assigned number that has no meaning, so it can't be linked back to a person and ensure our system is compliant with ethics. This enables us to run action recognition on each individual over multiple frames.

To better understand the context of the individual's movement, we implemented an action recognition machine learning algorithm to recognise what action each individual was doing and to identify person-to-person interactions. Multiple Multi-Person Skeleton-based spatiotemporal action recognition AI models were trained and tested using the STGCN++ backbone on the NTU60_XSub_2D dataset. These AI models varied in their frame sampling strategies to find the model best suited to the hardware capabilities of the edge device and provided the most accurate results. A Skeleton-based spatiotemporal Action Recognition Algorithm was chosen over other AI models as it consistently required less processing time than other models that used the whole frame as the input. Further, since the model sampled the pose estimation over multiple frames, we were able to get a better understanding of the action they were doing, as opposed to looking at only a single pose estimation. With the multiple frames, we can recognise more complex actions such as waving, standing up, drinking, etc. The algorithm can also take in the pose estimation data of multiple people to detect how 2 people interact with each other, such as shaking hands, patting on the back, etc. The main limitation of this method is that since there is no image data used as input, there is no way to understand how they interact with different objects while doing these actions.

To compensate for this, we add an object detection machine learning algorithm to the system. The object detector identifies the object being interacted with, while the action recognition determines the specific manipulation (Figure 16). For instance, if the object detector locates a basketball in the individual's hand and the action recognition detects the throwing action, the final output would be 'throwing the basketball'.

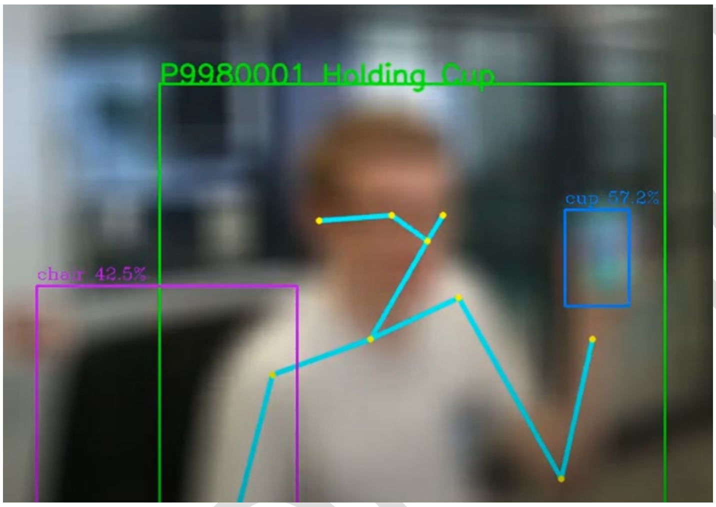

Figure 16. Image from the privacy-compliant video feed illustrating the system's recognition of the individual's activity as 'Holding Cup'

For the system to be scalable with multiple cameras to cover the whole building, the output from each camera is transmitted to a centralised lightweight server. The data flow between each edge device and the lightweight server is controlled using the MQTT protocol. The MQTT protocol is used since it uses the publish/subscribe method which makes it easier to manage a lot of devices and the data flow. The mobility data is collected at the lightweight server to filter out outliers and merge duplicate points. This is done to get the mobility information of the whole building, which is then transmitted to the 3D visualiser and database for further analysis.

Spatial visualisation and interaction with sensing data and simulation results

To address the diverse needs of users in a digital twin application, several key design requirements must be prioritised. One of the primary needs is for effective spatial visualisation. Users require a clear and detailed 3D representation of the building, which includes the ability to navigate through the model efficiently. The design must incorporate various navigation functions to help users move smoothly within the model and avoid confusion. Additionally, users should be able to access a comprehensive list of building elements directly from the interface, enabling them to quickly find and interact with specific components. This detailed and organised visualisation is crucial for users across different roles to interact with the DT effectively. A significant feature that meets user needs is the integration of real-time sensing data into the 3D building model. Stakeholders need to access real-time information from sensors placed throughout the building, providing insight into various parameters like temperature, energy usage, or humidity levels. The application should also allow users to select a specific range of time to analyse historical data, giving them the flexibility to view trends or pinpoint issues over specific periods. This feature enhances users' ability to monitor building performance and make data-driven decisions.

By enabling both live and retrospective data visualisation, the system accommodates both real-time operations and long-term planning. To improve usability, the application must offer customisation options. Different stakeholders may have different goals, whether they are engineers focused on system efficiency or managers interested in overall performance metrics. Allowing users to selectively enable or disable various plugins or extensions based on their specific needs ensures that the interface remains focused and uncluttered. Another essential design requirement is the cross-platform accessibility of the digital twin. The system must be web-based, allowing it to be accessed from any device, including desktops, tablets and mobile phones, without requiring specific hardware. This flexibility ensures that stakeholders can interact with the digital twin whether they are in the office or on-site. Finally, the digital twin must incorporate role-based access control to manage the varying needs and permissions of different stakeholders. The application should define various access levels, ensuring that users only have access to the features and data relevant to their role.

To effectively address the design requirements of the digital twin application, we leveraged the Viewer SDK (Software Development Kit) from Autodesk Platform Services (formerly Forge). The Viewer SDK allows us to build a web-based visualisation application with the ability to show the building model in full detail and to represent sensing data in real-time and in various effective formats. Using the Viewer SDK, we developed several key features through extensions to address the diverse needs of users in the front-end visualisation application.

3D Model Visualisation: Users can visualise a comprehensive 3D model of the building, allowing them to explore it in detail. This feature includes the ability to obtain a complete list of all building elements involved in the design along with roaming around the model. By accessing this information directly from the interface, users can quickly identify and interact with specific components, facilitating a more thorough understanding of the building's architecture and systems.

Real-Time and Historical Data Visualisation: The application integrates data obtained from various sensing devices installed throughout the building, enabling users to visualise this information in real-time. This feature provides insights into critical parameters such as temperature, CO_2 and humidity levels, occupancy status of different zones in the model and the thermal comfort of the building users, which enhances users' understanding of the building's operational state. Further, the application allows users to select specific time ranges to analyse historical data, making it easier to track trends and pinpoint issues over designated periods. This capability supports both immediate decision-making and long-term planning.

Customisable Visualisation Functions: To improve usability and focus, the application includes options for users to toggle various visualisation functions on or off. This flexibility allows users to customise the interface according to their specific needs, whether they are looking to streamline their view for better understanding or delve into more complex data. This feature is especially beneficial for stakeholders with differing objectives, enabling engineers to concentrate on system efficiencies while allowing managers to monitor overall performance metrics.

Multiple Data Representation Methods: The digital twin application offers various methods for representing information obtained from sensory devices, including charts, tables and heatmaps. This flexibility in data visualisation allows users to choose the format that best suits their needs and preferences. For instance, charts can be used for quick trend analysis, enabling users to grasp changes over time at a glance. Tables provide detailed data listings, allowing for in-depth comparisons and analyses of specific parameters. Heatmaps visually represent data distributions, making it easier to identify areas of concern or interest at a glance. By supporting multiple representation methods, the application enhances user comprehension and facilitates more informed decision-making based on the sensory data collected.

Extensions and Plugins: The digital twin application is designed with flexibility in mind, offering various extensions and plugins tailored for different applications. Users can activate or deactivate these features based on their specific tasks or goals, ensuring that the interface remains uncluttered and relevant to their needs. This modular approach enhances the application's adaptability, making it suitable for a wide range of users and use cases.

Cross-Platform Accessibility: Being a web-based application, the digital twin can be accessed from multiple devices, including desktops, tablets and mobile phones. This design choice eliminates the need for specialised hardware, allowing users to interact with the application from various locations. The 3D model is rendered in the cloud, ensuring smooth performance and easy access, whether users are on-site or working remotely.

Enhanced Navigation Functions: To facilitate efficient exploration of the 3D model, the application includes several navigation functions designed to help users move through the model seamlessly. These tools allow users to zoom, pan and rotate the view, making it easier to inspect specific areas and understand the relationships between different building elements. By improving navigation, the application reduces confusion and enhances user engagement with the digital twin.

These carefully implemented features, as shown in Figure 17, collectively ensure that the digital twin application meets the diverse needs of its users, providing a powerful, flexible and accessible platform for managing building data and performance effectively.

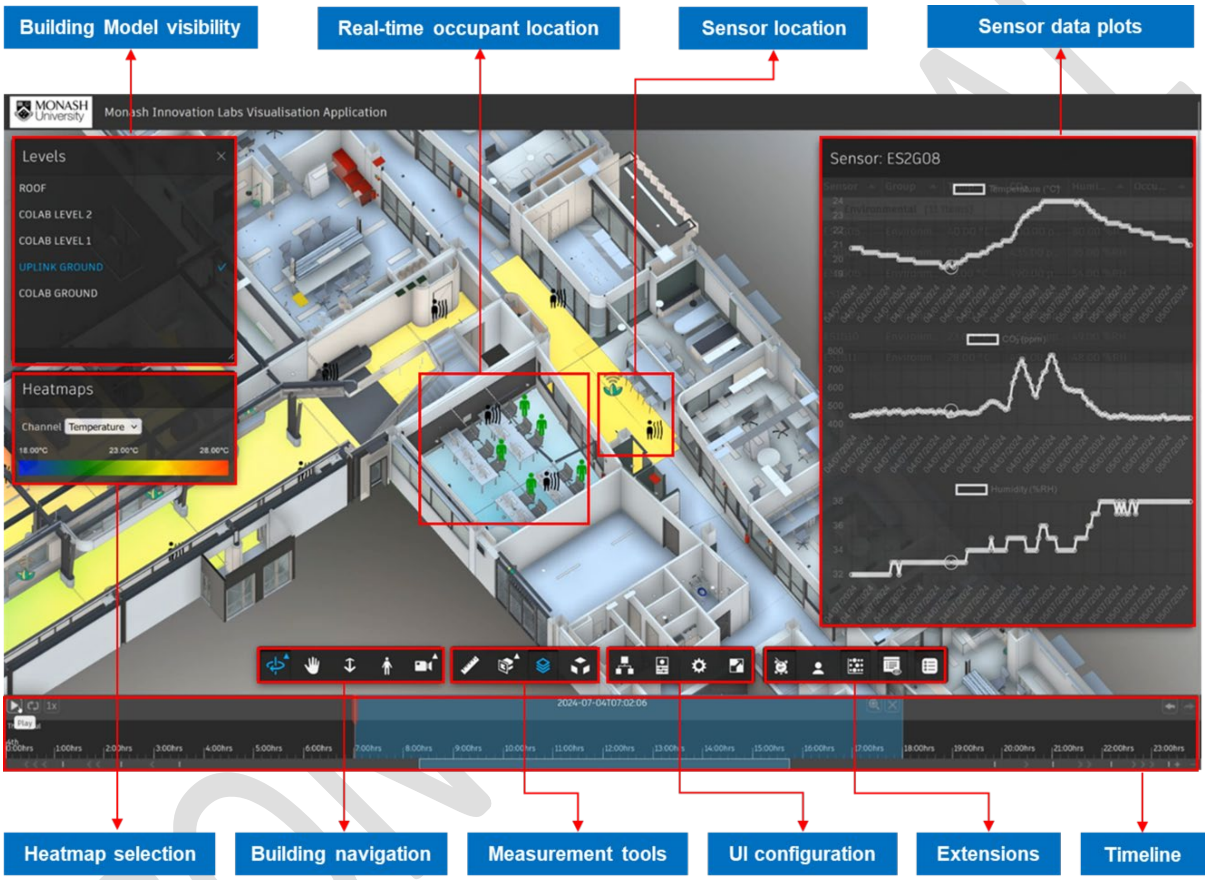

Figure 17. User interface features of MIL-DT visualisation application

To support the front-end visualisation features, a purposeful back-end data handling pipeline was developed. As shown in Figure 18, the back-end system is primarily responsible for processing the data, while our front-end consists of 2 systems: one for visualising historical data and the other for displaying live data. Specifically, due to the varying sample frequencies of different sensors, each sensor will upload the values to our primary database periodically. Subsequently, we established a platform developed by Java that retrieves data from the primary database and stores it in our secondary database. Meanwhile, these data are published through a middleware, MQTT, which is subscribed by the front-end application for live data visualisation. Additionally, our platform provides an interface for our historical data viewing application in the front end to access historical data.

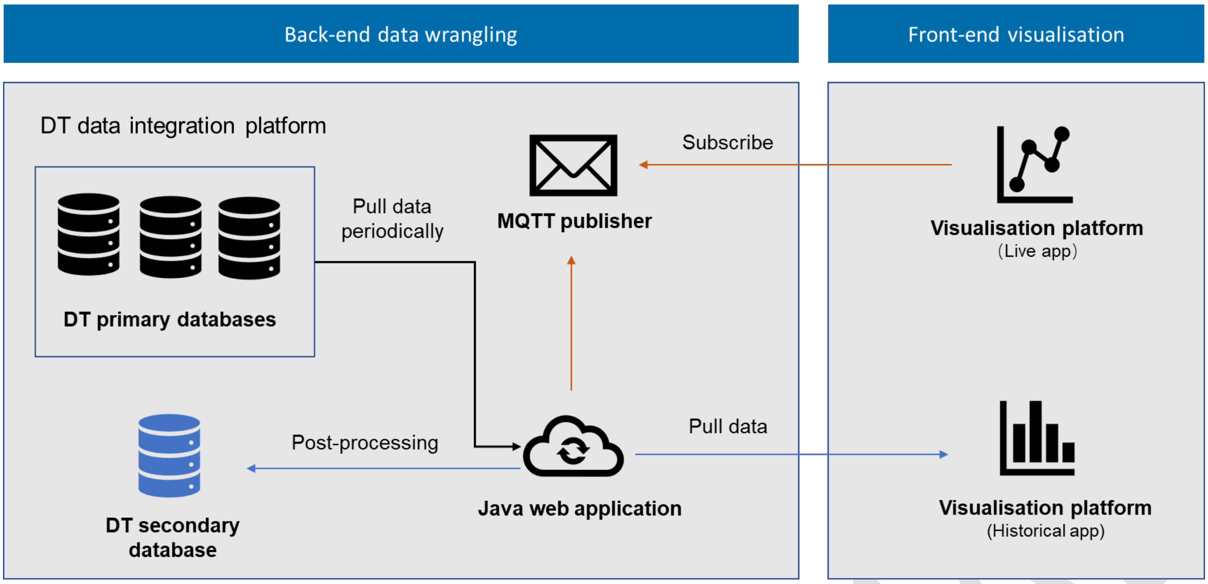

Figure 18. Back-end and front-end configuration of the visualisation platform

The reason why we don’t allow our live application to access the data from the primary database directly is due to the large volume of data stored in it. if we allowed the live application to retrieve data directly from the primary database, it could cause significant delays, negatively impacting the user experience. Therefore, we established a Java web application and MQTT to serve as a cache, enabling our live application to display real-time data with lower latency. moreover, the purpose of the secondary database is to reconstruct the data obtained from the primary database. this step not only helps us better analyse the data we are interested in but also reduces the required storage used by our secondary database, thereby lowering latency when retrieving data for our historical application.

For example, our primary database stores the humidity, temperature, PM2.5, PM1, PM4, PM10, low volatile organic compounds, formaldehyde, pressure, battery and CO_2 for each environmental sensor at any moment, but we are primarily interested in the CO_2, temperature and humidity. In this case, we only save this kind of data in our secondary database.

Together with other sensing dashboards, the visualisation application is deployed in the MIL-DT control room to allow stakeholders to interact with the dynamic building model enriched by sensing data and analytic results (Figure 19).

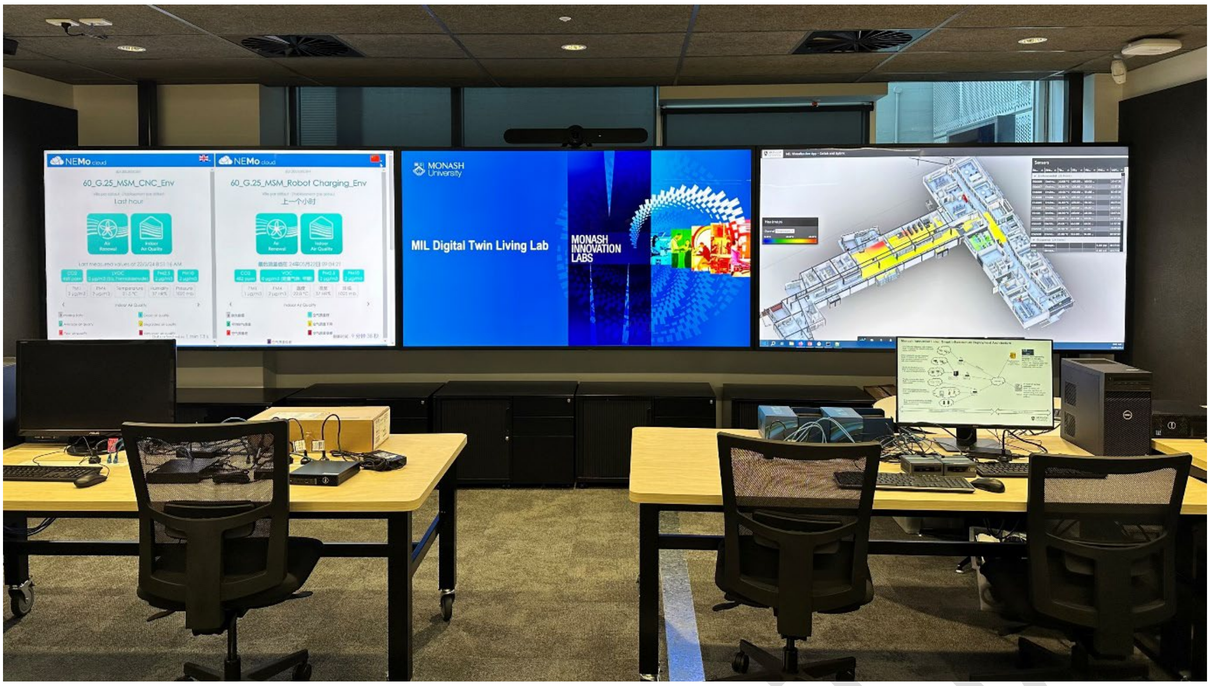

Figure 19. MIL-DT control room for interacting with building model and sensing data

3.4. DT development process and stakeholder engagement

In the development of MIL-DT, we employed an agile development framework to facilitate design flexibility, collaboration and rapid delivery. At the core of this framework was a cross-disciplinary development team, comprising a project manager, technical specialists, an academic advisory group and a DT user group. The project manager was responsible for creating the development plan, overseeing the process and progress and facilitating communication and collaboration among team members. The technical specialist team, consisting of system architects from Monash and the industry partner AWS, as well as 3 software developers, was tasked with creating the system architecture and designing and implementing solutions for the functional components of MIL-DT. The academic advisory group included academics from various fields who had an interest in the design or usage of MIL-DT from a research perspective. They worked closely with the technical specialist team to ensure the novelty and relevance of the developed solutions. The DT user group, represented by MIL users and asset managers, advised on the desired use cases and applications to be targeted by MIL-DT. Multiple workshops among the project development team took place at different development stages to clarify the user demands, understand implementation constraints and refine development objectives. Most importantly, these engagements helped identify the key applications that MIL-DT targeted.

Guided by the system architecture and continuous feedback from the stakeholders, the development of the MIL-DT underwent 3 phases, each designed to test and integrate key DT components in each layer (Figure 20). Phases 1 and 2 focused on ensuring a reliable and effective system, culminating in phase 3, which aimed to implement the system across the entire facility. In phase 1, a single room served as a staging lab where all 5 types of sensors were deployed in small quantities to test and refine the installation and communication methods. A data integration platform was established to federate data from different sensors and store them in a spatially mapped data structure. Additionally, we piloted the method for creating a high-fidelity as-built spatial model and a prototype 3D web user interface for visualising and interacting with sensing data. In phase 2, the scope was expanded to a multi-room, multi-purpose space, the Makerspace, with a focus on identifying and addressing issues associated with scaling up. Finally, phase 3 aimed to fully integrate all DT components and conduct case studies to assess the MIL-DT's performance and efficacy in the targeted applications.

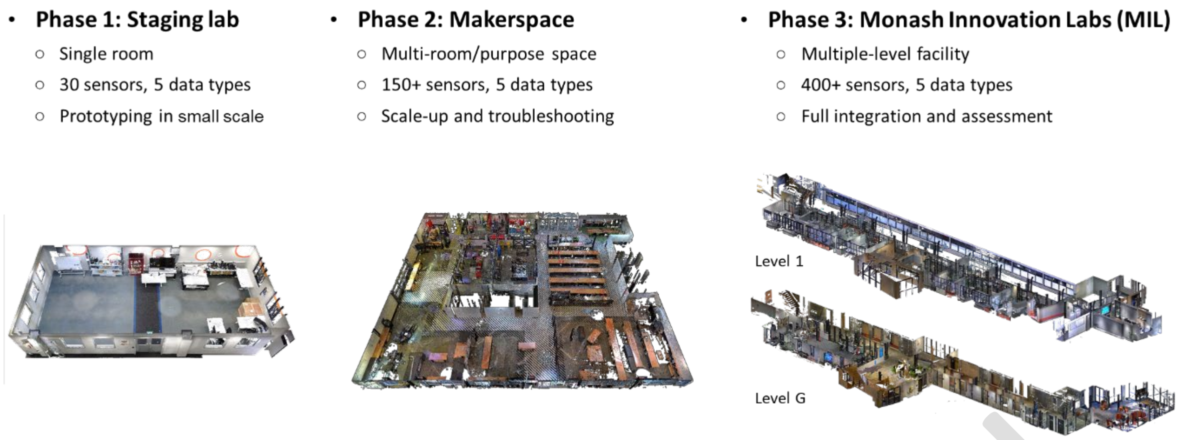

Figure 20. Three-phase development plan for MIL-DT

4. MIL-DT CASE STUDIES

To demonstrate the capabilities of MIL-DT in facilitating the targeted applications, 3 case studies were conducted on 1) HVAC control for energy efficiency, 2) workplace safety and health risk detection and 3) personal thermal comfort analyses. These applications concern building energy efficiency and the wellbeing of building occupants. The following sections present the application background, implementation approach and DTs impact assessment.

4.1. Case Study #1: DT-based building HVAC control for energy efficiency

Effective control and operation of HVAC systems are essential for enhancing building energy efficiency and sustainability [35]. Properly managed HVAC systems can significantly reduce energy consumption by optimising heating and cooling processes, ensuring energy is used only when and where needed [36]. This approach not only lowers operational costs but also minimises environmental impact by reducing greenhouse gas emissions. Additionally, efficient HVAC systems improve indoor air quality and occupant comfort, which are vital for the overall wellbeing of building users [37].

Recent advancements in IoT and CV have introduced occupancy as an input for HVAC control, creating a reactive feedback mechanism. For example, a study demonstrated an HVAC strategy that uses real-time occupancy levels (i.e., the number of occupants) as an input, with a rule-based system adjusting the HVAC operating status, resulting in a 15% daily energy savings [38]. Researchers have utilised various sensors, such as passive infrared sensors [39], door reed switches [40], Wi-Fi [41] and cameras [42], to detect occupancy for reactive control methods. However, inaccurate detection remains a challenge. For instance, results indicated that using Wi-Fi networks to detect occupancy achieves only 86% accuracy, leading to false triggers for HVAC operations [41]. Despite potential inaccuracies in data collection, the energy savings are promising, with reductions in energy use ranging from 7% to 26% compared to control methods focusing solely on temperature and CO_2 levels [43]. It is anticipated that with more accurate, real-time occupancy data, a DT-enabled, occupancy-driven HVAC control will further reduce energy consumption while maintaining indoor environment quality and occupant comfort.

In MIL, the HVAC operation currently employs a traditional reactive control strategy, adjusting the system's operating status based on sensed temperature and CO_2 concentration. The BAS allows for continuous monitoring and remote control of HVAC assets in MIL. As illustrated in Figure 21, a damper regulates the intake of external fresh air, while a fan drives air through heating and cooling coils before being supplied to the indoor space. Their operation is governed by predefined thresholds for CO_2 concentration and temperature. For instance, the damper activates when CO_2 concentration exceeds 800 ppm and deactivates when it falls below 600 ppm. Similarly, temperature control is managed by the fan, which activates below 21°C and deactivates above 24°C during winter. However, this strategy can result in excessive energy consumption and inefficiency if the space is not fully occupied. As proposed by the asset managers during the workshop, it is ideal for the thresholds to be adjustable according to anticipated space utilisation, with HVAC assets automatically controlled based on actual space occupancy. Therefore, in this case study, we investigated how effectively the MIL-DT could facilitate an adaptive HVAC control strategy by leveraging the real-time space utilisation insight.

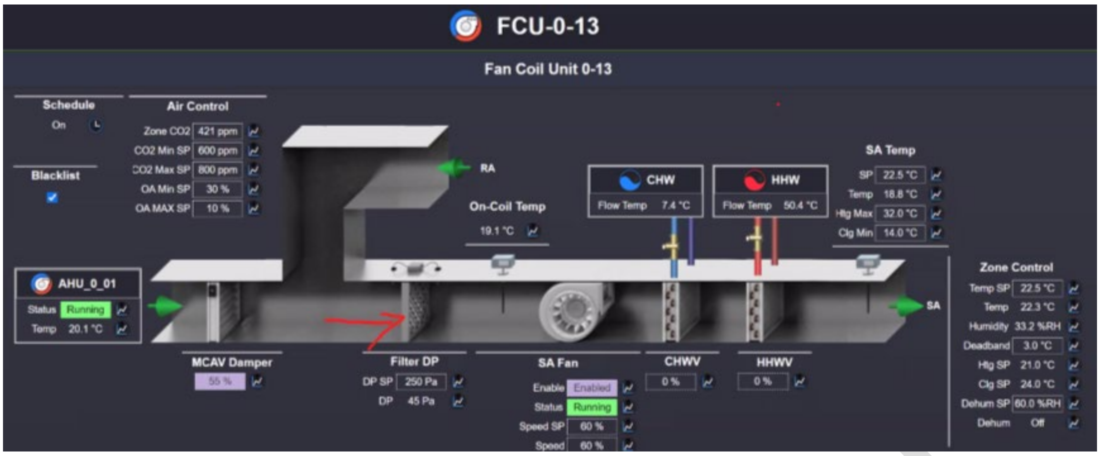

Figure 21. BMS interface for HVAC control of a fan coil unit (FCU) in MIL

The aim of this case study is to demonstrate the potential energy savings achieved using a DT-based HVAC control system. Figure 22 illustrates the experimental design. The experiment was conducted over 4 days in early July, during which energy consumption for heating, cooling and fan operation, as well as various environmental data, were collected. For 2 of these 4 days, the traditional HVAC control method (referred to as the baseline) was used, while the DT-based approach was applied on the other 2 days. The schedule remained consistent across all 4 days, with 3 different occupancy scenarios each day: 2 hours of low occupancy (one occupant in the MIL), 2 hours of high occupancy (5 occupants in MIL) and the remaining hours unoccupied.

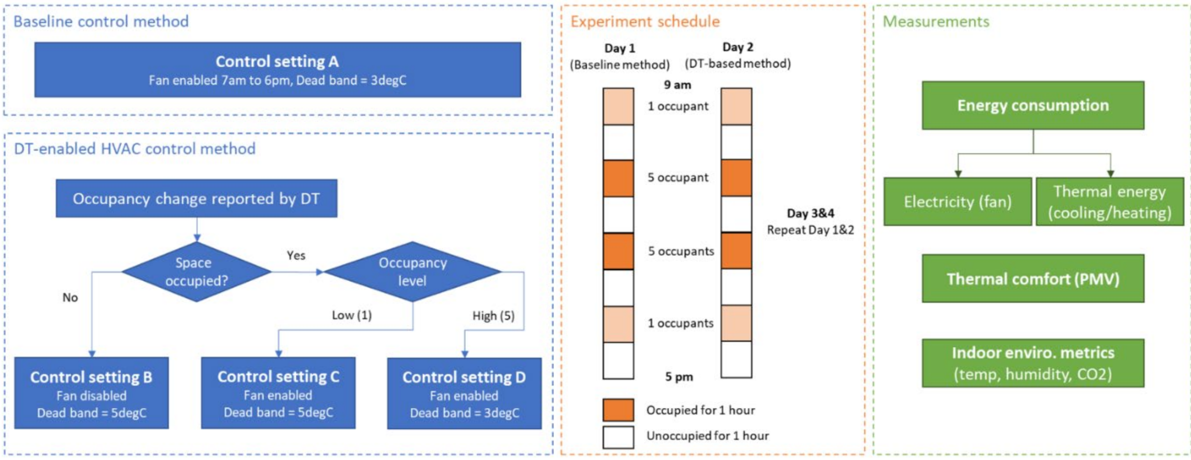

Figure 22. Experimental design illustrating the 2 HVAC control methods (left), occupancy schedule (middle) and data measurements (right)

Under the baseline control, the fan in the HVAC system operated continuously from 7 am to 6 pm, maintaining a temperature deadband of 3°C regardless of occupancy levels. The deadband refers to the temperature range within which the system does not activate heating or cooling, allowing for some fluctuation before any adjustments are made. In the DT-based control, the fan was disabled when no occupants were detected in the MIL, with the deadband set at 5°C. When occupancy was detected, the fan was activated and the deadband was adjusted based on occupancy: it remained at 5°C for low occupancy and was reduced to 3°C for high occupancy. All other parameters, such as the set temperature for triggering heating and cooling and the CO_2 concentration threshold for controlling the HVAC system, were kept constant between the 2 control strategies.

Figure 23 shows a screenshot of a real-time DT visualisation platform. The platform provides a clear visualisation of occupancy levels in the MIL space and monitors changes in key environmental factors over time.

Figure 23. Real-time DT visualisation platform showing a temperature spatial heatmap and trendline plots

Figure 24 shows the heating energy load (orange bars) and fan energy consumption (blue bars) for each of the 4 experimental days. On days 2 and 4, the HVAC system operated under DT-based control, resulting in significantly lower heating energy load and fan energy consumption compared to days 1 and 3, where the traditional control approach (baseline) was used.

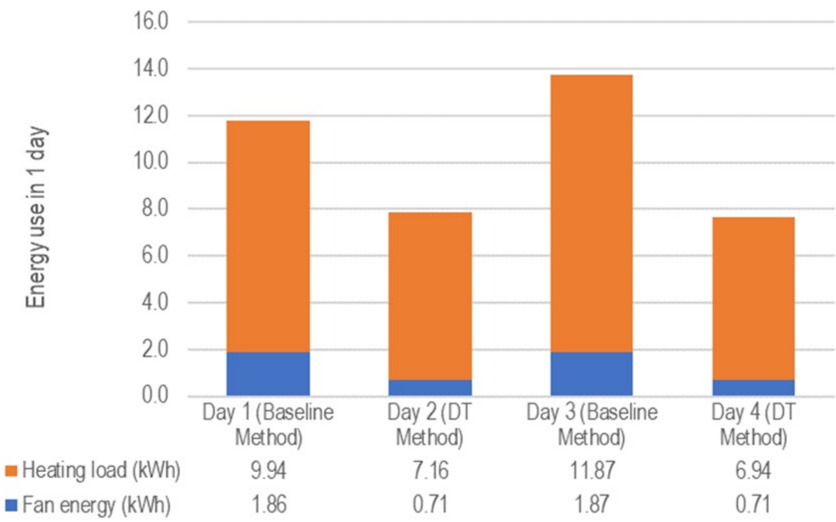

Figure 24. Heating energy load (orange bars) and fan energy consumption (blue bars) for each of the 4 experimental days

As summarised in Table 4, the average daily energy savings in the MIL lab room was approximately 5 kWh. When these results are scaled to the entire MIL and extended across the full heating season, this translates to potential savings of around 18 MWh. To provide context, Monash's Clayton campus consumes nearly 2,000 MWh of electricity for heating each heating season. If most campus buildings (assuming 40 buildings of similar size to the MIL) were to adopt DT-based control, total heating energy consumption could be reduced by approximately 735 MWh per year, representing a reduction of more than one-third from the 2,000 MWh baseline.

Table 4. Energy savings at 3 scales: for 1 FCU over 1 day (measurement data), for the entire MIL building over 1 day (estimates based on measurement data) and for the entire MIL building over a heating season (estimates based on measurement data)

	Fan energy (kWh)	Heating load (kWh)	Total (kWh)
Energy saving for 1 FCU unit for 1 Day*	1.2	4.1	5.2
Energy saving for a building for 1 Day**	62.6	220.0	282.6
Energy saving for a building for a heating season***	4071.6	14300.1	18371.7

Assumptions:

**The reported number represents the average savings calculated from the experimental data. The energy for heating is measured as the heating load, excluding the efficiency of the heating devices. The air constant is 1.213 kJ/kg-K. The daily average outdoor air temperatures were 8.49°C, 7.50°C, 7.70°C and 9.48°C for Days 1 through 4, respectively.*

***There are a total of 54 Fan Coil Units (FCUs) in this building, all of which have the same size, amp draw and speed.*

****All spaces are in operation 5 days a week, for a total of 13 weeks during the heating season.*

4.2. Case Study #2: Workplace safety and health risk detection

Workplace safety and health is another critical use case identified by asset managers and building users during stakeholder engagement. Unsafe behaviours, such as violations of laboratory protocols (e.g., eating or drinking near lab equipment) and ergonomic hazards (e.g., improper lifting postures for heavy loads, prolonged sitting), can compromise the safe operation of the building and laboratories, as well as the safety and health of occupants. The management of safety and health risks typically relies on periodic training and self-reporting. However, these methods can be inconsistent and unreliable due to human error and the absence of real-time monitoring.

MIL-DT detects and analyses these unsafe behaviours based on the skeleton data of occupants retrieved from images and videos. Extracting skeleton data is a mature technique in CV, with significant advancements in recent years. Techniques such as OpenPose [44] and MediaPipe [45] have proven highly effective in accurately detecting and tracking skeleton key points (e.g., wrists). With skeleton data, it is possible to understand various occupant behaviours, such as drinking, eating and using mobile devices [46]. Additionally, these techniques enable the identification of awkward postures that lead to musculoskeletal disorders (MSDs), such as improper bending, lifting and prolonged sitting [47-49].

A key feature of MIL-DT is its focus on occupants' behaviour. The in-house algorithm specialist developed a CV model to extract skeleton data from camera footage. The OpenPose Standard Library was employed to recognise human behaviours, such as drinking, eating and sitting. To ensure lab safety, digital perimeters were set around key laboratory equipment, such as robotic arms and CNC machines, to identify violations of lab management protocols. As illustrated in Figure 25, the system is able to detect actions violating lab rules (i.e., eating/drinking near machines) and ergonomic risks (i.e., bending the back when lifting) in real-time. These detections are then compiled into an ergonomic report that summarises the frequency and types of unsafe behaviours observed, providing actionable insights for improving workplace safety and reducing the risk of injuries. This report serves as a valuable tool for building users and health and safety officers to implement targeted interventions and ensure a safer working environment.

Figure 25. Computer vision-based detection of workplace safety and health risks (left: eating/drinking near a machine; right: bending the back when lifting heavy load)

4.3. Case Study #3: Personal thermal comfort analyses

Thermal comfort, defined as an occupant's perceived sensation of their surrounding environment, plays a critical role in the operational principles of HVAC systems in buildings [50]. MIL asset managers exhibited great interest in obtaining thermal comfort data to better understand occupant satisfaction and improve energy efficiency. MIL users are also keen to see more adaptive heating and cooling in their spaces instead of pre-programmed control based on a rough estimate of occupancy and environmental conditions. Academics involved in this project are also keen to leverage the thermal comfort data to perform data-driven methods to predict building thermal loads.

Traditionally, measuring thermal comfort requires methods that interrupt the daily routines of occupants. These include the subjective reporting of thermal sensations via mobile applications [51] and the employment of wearable physiological sensors to monitor individual thermal comfort levels [52]. While these methods have proven effective in capturing nuanced and accurate data, the measurement is sophisticated and thus, they cannot support real-time decisions of asset managers. An alternative thermal comfort indicator is the PMV index, as delineated in ASHRAE Standard 55 [53]. The PMV model encapsulates thermal comfort by considering a confluence of 6 personal and environmental parameters: air temperature, mean radiant temperature, air speed, humidity, clothing insulation and metabolic rate. The PMV index predicts the mean response of a large group of people on a 7-point thermal sensation scale, from +3 (hot) to -3 (cold), where 0 is neutral [55]. According to the National Construction Code, the Green Star certification of university buildings (Class 9b) requires a PMV range of -1 to +1 to be achieved in at least 95% of the floor area of all occupied zones for no less than 98% of the building's annual operation hours. It should be noted that this approach inherently assumes a homogeneity among occupants (e.g., a standard value of occupants' metabolic rates) [54], which cannot accurately reflect the diversity of individual behaviours in multifunctional spaces, which accommodate a range of activities from meetings and desktop work to the manufacturing operations.

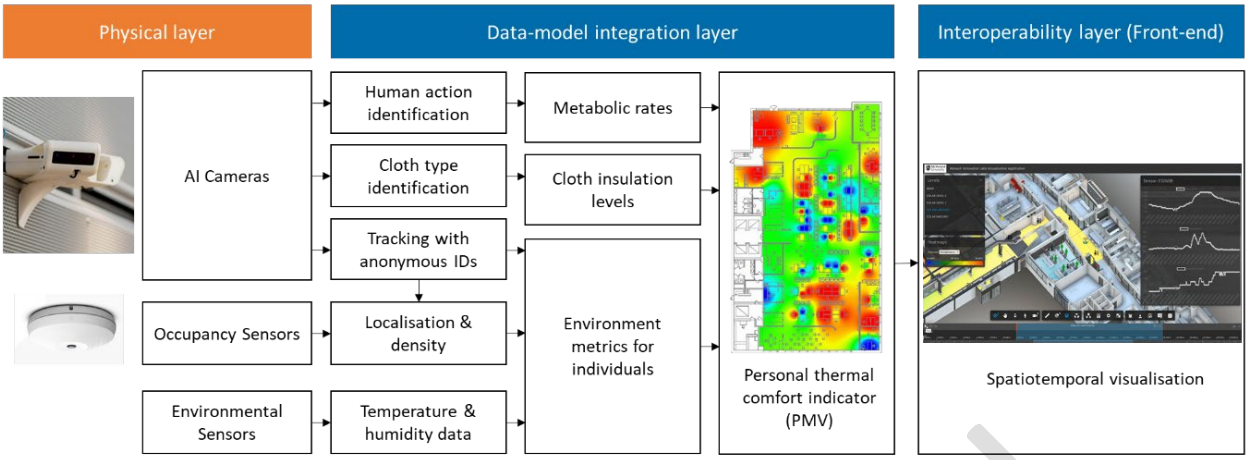

Figure 26. Framework of individual PMV calculation and visualisation

To address these limitations of PMV, MIL-DT employs privacy-compliant computer vision techniques to identify the clothing types of occupants and their actions based on skeletal postures without revealing the identity of the person being monitored. This approach allows for an individual-level interpretation of clothing insulation values and metabolic rates, which are integral to calculating an individual's PMV. This calculation also incorporates environmental variables such as temperature, relative humidity and air velocity obtained by environmental sensors. The computational process is executed within the DT's primary database, subsequently disseminating the results to a data visualisation platform (Figure 26). This platform graphically represents occupants' locations alongside their personal PMV, offering a dynamic and insightful tool for real-time decision-making, personalised recommendations and the collection of high-quality research data (Figure 27).

Figure 27. Real-time thermal comfort measurement and visualisation in MIL-DT

5. DISCUSSION AND RECOMMENDATIONS

5.1. Insights and lessons learned in DT design and development

During the development of MIL-DT and the implementation of various advanced technologies, the project team encountered numerous challenges and opportunities that provided a wealth of learning experiences. Through meticulous planning, execution and continuous evaluation, several key lessons were learned and significant insights were generated. These insights encompass a broad range of areas, from user engagement to data mapping and privacy and ethics considerations. The knowledge gained from these experiences is not only reflective of the project's successes and areas for improvement but also offers a useful guide for future DT initiatives.

Proactive and continuous stakeholder engagement

The first and probably the biggest lesson learned from this project is the importance of user feedback in shaping the design and functionality of the DT. Engaging stakeholders early in the development process and seeking their feedback at multiple stages helped identify key demands and development priorities, leading to a more user-centric design and efficient development process. This iterative approach allowed the project team to refine key functional components and continuously improve their performance based on real-world usability, ensuring that the application effectively met the diverse needs of its users.

By involving users from the outset, the project team was able to gather invaluable insights into the practical requirements and preferences of different stakeholders. This proactive engagement not only fostered a sense of ownership and collaboration among users but also highlighted potential issues and areas for improvement that might have been overlooked otherwise. Regular feedback sessions and user testing phases were instrumental in fine-tuning the system, making it more intuitive and responsive to the actual working conditions and expectations of its end-users.

Additionally, the integration of various data representation methods underscored the necessity of flexibility in visualisation tools. Different stakeholders often require distinct ways to visualise and interpret data and information, depending on their specific roles and objectives. For instance, engineers might need detailed technical views, while managers might prefer high-level summaries and dashboards. By accommodating these diverse needs, the project ensured that all users could effectively utilise the DT to make informed decisions and optimise their workflows.

Further, the emphasis on user feedback and flexible visualisation tools contributed to a more adaptable and scalable system. As new requirements emerged and technologies evolved, the DT could be easily updated and expanded to incorporate additional functionalities and data sources. This adaptability not only enhanced the system's longevity but also ensured that it remained relevant and valuable to its users over time.

Consistent naming and mapping approach

Another crucial takeaway is the necessity of harmonising naming conventions and implementing a standardised spatial mapping approach for data gathered by various sensors. When the quantity of sensors mounts up to hundreds, sensor names must reflect not only their type and the data they collect, but also the location where they are installed. This level of detail is essential for maintaining an organised and efficient system.

For instance, many applications, such as thermal comfort analysis and safety risk detection, rely heavily on the location attribute of sensors. Accurate spatial mapping allows for precise interpolation of temperature heatmaps, which is vital for assessing and ensuring thermal comfort in various environments. Additionally, in safety risk detection, knowing the exact placement of sensors is critical for calculating the clearance of humans and their surroundings, thereby preventing accidents and ensuring a safe operational environment.

Moreover, a unified naming convention and standardised spatial mapping facilitate better data integration and interoperability between different systems and platforms. This standardisation helps reduce errors, improve data accuracy and enhance the overall reliability of the system. It also simplifies the process of data analysis and reporting, making it easier for stakeholders to make informed decisions based on the collected data.

Privacy and ethics considerations

Monitoring and tracking building users can be sensitive and potentially intimidating if not managed with the utmost care and supported by reliable technical solutions. This project places a high priority on ethical considerations, dedicating significant effort to consulting stakeholders and devising technical solutions that ensure privacy and ethical requirements are rigorously met. As detailed in Section 3.3, a privacy-compliant framework was implemented to de-identify individuals and conceal their appearance using advanced computer vision techniques and an edge computing solution.

In addition to these technical measures, it is crucial to maintain transparency with building users regarding data collection practices. Users are thoroughly informed about the types of data being collected, the methods of data collection and the specific applications that will utilise this data. This proactive communication helps to build trust and ensures that users are aware of and comfortable with the data collection processes.

By integrating these comprehensive technical and communicative approaches, the project not only meets but exceeds privacy and ethical standards, fostering a secure and trustworthy environment for all building users. This dual focus on technology and transparency is fundamental to the successful implementation and operation of the DT, ensuring it serves its intended purpose without compromising user privacy or ethical standards.

5.2. Design and development framework for DT implementation

Based on the sights generated and lessons learned throughout the development of MIL-DT, we propose a design and development framework to guide the future implementation of DT technologies for building operation purposes. Figure 28 illustrates the fundamental design and development steps with details of considerations and criteria that should be incorporated into key steps.

The goal of the first phase is to define the scope of the DT with regard to the key applications it is expected to support. This is done by engaging stakeholders of these applications and, based on their respective data, analytics and visualisation needs, defining the DT specifications that satisfy these needs. The second phase features an iterative development and staging process where the DT architecture is materialised by creating key functional components and optimising them by testing and incorporating feedback from stakeholders. Key performance metrics are assessed against the design specifications before moving on to the next phase. Once the performance of the DT is confirmed in the staging space, the third phase upscales the implementation to the full scope. As the sensor quantity and spatial complexity increase, challenges may present in installation, calibration and data mapping during deployment and commissioning. When the DT is in operation, ongoing maintenance must be in place to ensure all hardware and software components function without fault or performance interruption. Continuous engagement with stakeholders should also take place to identify improvement and new demands.

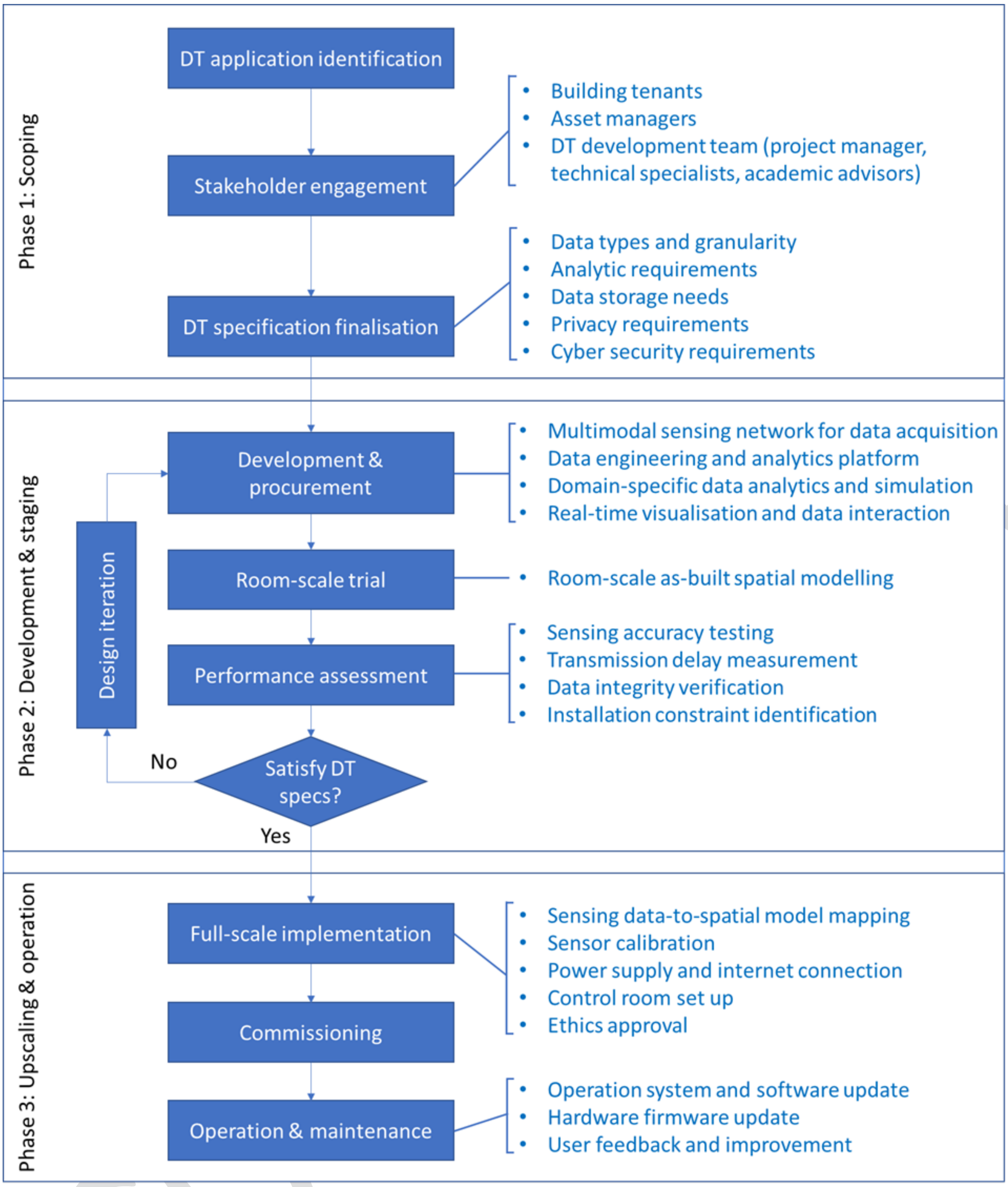

Figure 28. Design and development framework for DT implementation

6. CONCLUSIONS AND FUTURE RESEARCH

The design and development of DTs for building operation have been attracting increasing interests from both academia and the industry. DTs are promised to capture and reflect real-time conditions of building systems, spaces and occupants, which could assist decision-making in various essential building operations. This project aims to explore the design strategy of DTs, understand the implementation challenges and make recommendations to future DT developments, for building operation. This report presents the design requirements, development considerations, detailed implementation of a building-scale DT (MIL-DT) for a multi-function 2-storey building at Monash University. The benefits of MIL-DT in supporting energy-efficient HVAC control, workplace health and safety and thermal comfort analysis are demonstrated through 3 case studies. Throughout the design and development of MIL-DT, several key lessons were learned and significant insights were generated. By understanding and applying these lessons, owners and developers of future DT projects can enhance their strategies, avoid common pitfalls and achieve more efficient and effective outcomes. These insights could prove invaluable, serving as a foundation for innovation and excellence in the evolving field of DT technology.

At the end of this project in collaboration with AWS, we identified several promising directions for future research in DT for building operations, which the project team is eager to explore in future projects. The first 2 directions are related to expanding the functions of DT to better support user interaction. The last one concerns exploring new applications of DT in building operations and management tasks.

Future research should explore the integration of generative AI in data query and anomaly detection within DT systems. Generative AI has become very powerful in understanding questions posed in natural language (i.e., oral questions) and translating them into machine-understandable queries. This capability could potentially remove the technical barriers when interacting with the DT, making it more accessible to a broader range of users, including those without technical expertise. By enabling more intuitive and user-friendly interactions, generative AI can enhance the overall usability and effectiveness of DT systems. In addition to facilitating interaction, Generative AI models, such as generative adversarial networks (GANs) and variational autoencoders (VAEs), can be trained to detect anomalies by learning the normal patterns of sensor data. When new data deviates significantly from these learned patterns, the model flags it as an anomaly. These models can also cross-validate sensor data by comparing the outputs of multiple sensors measuring the same or related parameters. For instance, if one sensor's readings are inconsistent with those from other sensors, the AI can identify this discrepancy as a potential error.

Another promising direction is the development of advanced user interfaces that leverage AR and VR technologies. These interfaces can provide immersive and interactive experiences, allowing users to visualise and manipulate DT data in real-time. For instance, AR technologies can offer in-situ data visualisation by superimposing data or simulation results, such as heatmaps, at corresponding locations in the real world. Imagine a building manager using AR glasses to see a heatmap of energy consumption overlaid on different floors of a building, enabling them to identify areas with excessive energy use and take corrective actions immediately. Such advancements can significantly improve user engagement and facilitate better decision-making by providing a more intuitive understanding of complex data. By making data more accessible and easier to interpret, AR and VR technologies can help users identify patterns, trends and anomalies that might be missed with traditional 2D interfaces.

Apart from the 3 applications investigated in this project, many other applications could potentially benefit from DTs. One promising application is the prediction and assistance of egress during emergent situations. The accuracy of existing egress modelling methods depends on several assumptions, including space occupancy, occupant behaviour, route choice and crowd dynamics. DTs can enhance these models by providing accurate data that represent the initial egress states and continuously updating these states based on real-time information. For example, sensors throughout a building can monitor the number of occupants, their locations and movement patterns. This data can be fed into the DT to create a dynamic and precise model of the current situation. As a result, more effective instructions can be provided to occupants to guide them during an evacuation, ensuring both safety and speed. For instance, in the event of a fire, the DT can analyse real-time data from smoke detectors, heat sensors and cameras to identify the safest and quickest evacuation routes. This information can then be communicated to occupants via mobile alerts and digital signage, directing them away from danger and towards safe exits.

To further advance research in this application, it is crucial for the DT to integrate with the building's security system. This connection allows the DT to fetch real-time status data such as smoke alarms, exit availability and environmental conditions. By doing so, the DT can provide a comprehensive and up-to-date overview of the emergency, enabling more informed decision-making and efficient evacuation processes. By leveraging real-time data and advanced modelling techniques, DTs can offer a more accurate and responsive approach to emergency management, ultimately enhancing the safety and wellbeing of building occupants.

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