# BRIDGING THE GAP: BIM, DATA ANALYTICS, AND DIGITAL TWINS IN CONSTRUCTION LIFE CYCLE MANAGEMENT

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## ABSTRACT

The convergence of real-world applications with virtual simulations, driven by the Internet of Things (IoT), is poised to revolutionize the construction industry by significantly enhancing efficiency, safety, and sustainability. In this transformative landscape, the deployment of Digital Twin (DT) technology, which seamlessly integrates real-time sensor data into virtual models, emerges as a key driver for advancing Construction Life Cycle Management (CLCM). This evolution spans critical aspects such as ensuring structural integrity, enabling remote project monitoring, and optimizing operational processes. Building Information Modeling (BIM) serves as the foundational virtual framework, facilitating the initiation of Virtual Simulations & Modeling (VSM). Digital Twin (DT), building upon the BIM foundation, goes a step further by dynamically incorporating real-time data, offering dynamic reflections, and enabling simultaneous project monitoring. However, the integration of unstructured cloud data into the BIM-digital twin connection introduces complexities in real-time data synchronization and harmonization. Challenges related to efficient data acquisition highlight the importance of ensuring a continuous flow of real-time data from diverse sources. Effectively handling this dynamic and diverse information stream becomes crucial for maintaining the accuracy and responsiveness of the BIM-digital twin system. This study emphasizes a thorough literature review to extract insights from existing solutions. By understanding interconnectivity principles highlighted in the literature, the development of standardized protocols is guided, fostering seamless integration and ensuring a coherent flow of real-time data across BIM, digital twins, and diverse cloud-based sources. The study's outcomes not only include a synthesis of knowledge on the interaction of IoT, big data analytics, BIM, and DT applications in CLCM but also address challenges in data fusion. Furthermore, the review identifies innovative methods for data acquisition, registration, cleansing, segmentation, and object recognition, effectively handling unstructured point cloud data. By aggregating and analyzing data from various sources, this study contributes to a comprehensive knowledge base, empowering stakeholders to make informed decisions and embrace technological breakthroughs poised to transform the construction sector.

***Keywords:*** *BIM, big data analytics, construction life cycle management, digital twin, unstructured cloud data*

## 1. INTRODUCTION

The construction industry has historically relied on antiquated technologies to replace manual processes including project scheduling, monitoring, planning, and development due to inefficiency. Deriving the substantial advantages from integrating advanced technologies like the Internet of Things (IoT) for virtual simulation by the construction sector. This is because the technology can be utilized for project management, time management, and site plan creation (Santos & Assayag, 2022). Connecting a range of sensors and equipment on building sites allows data to be gathered, evaluated in real time, and created a virtual environment that facilitates decision-making and increases project efficiency overall. (Dosumu et al., 2023).

Furthermore, predictive maintenance can be made possible by integrating IoT and Digital Twin (DT) for big data analytics and virtual simulations. This enables early detection of equipment breakdowns and minimizes downtime (Jia et al., 2022). However, there are obstacles to overcome, like lack of training facilities, knowledge, and proficiency in these technologies, along with problems with network access and stakeholder participation in the building industry. To solve these issues and investigate the possibilities of this integration in the construction sector, more investigation is required (Raj, 2023).

Pre-construction model analysis and real-time project monitoring are greatly aided by modelling a virtual structure using Building Information Modelling (BIM) and DT deployment. This development makes it possible to create virtual copies of real assets or processes, which facilitates data analysis and scenario modelling (Abo-Khalil, 2023). DT and BIM may continuously update and enhance the system, enhancing its performance, by integrating sensors, IoT devices, and machine learning algorithms (Abo-Khalil, 2023). Applications of DT BIM in the transportation, power systems, and wireless communication networks, among other industries, have shown promise for improving system reliability, accelerating analysis speeds, improving prediction accuracy, and facilitating effective risk management (Ferrigno & Barsola, 2023; Jedermann et al., 2023; Madubuike et al., 2023). With the use of virtual models from BIM and DT offer a foundation for intelligent planning and deployment that makes successful and economical solutions possible.

BIM as virtual replicas of physical assets, and DT as real-time cloud connection with the replicas play a pivotal role in leveraging lifecycle management for construction projects. By providing dynamic, data-driven representations, they enable proactive decision-making and enhance understanding of complex systems through continuous monitoring and analysis.

In light of this, the review paper seeks to clearly define its goals by offering a thorough assessment of the current level of integration between DT, IoT, big data analytics, and BIM technologies in construction life cycle management (CLCM). It also makes it possible to comprehend the many difficulties in expanding CLCM using these technologies in detail. The study focuses on how CLCM connects with virtual environments by harnessing efficiency from top to bottom. This review aims to provide guidance for future research directions and practical implementations through a thorough analysis, paving the way for a future in construction management that is intelligent and driven by digital technology.

## 2. EVOLUTION OF CONSTRUCTION LIFE CYCLE MANAGEMENT (CLCM)

In the historical landscape, manual processes and disparate data sources hindered the efficiency of construction life cycle management. The advent of virtual simulation and modelling (VSM) technologies, driven by the interpretation through Building Information Modelling (BIM), brought a digital revolution. This transformation not only offered a cohesive digital representation but also fostered collaboration by unifying fragmented data. In the contemporary era, the imperative integration of BIM and digital twin technologies further elevates construction management. This symbiosis enables a holistic, data-driven strategy, ushering in an era where real-time insights, predictive analytics, and adaptive decision-making redefine the construction life cycle.

### 2.1 Role of VSM in CLCM

VSM technologies, such as Building Information Modelling (BIM) and digital twin, have evolved in the context of Construction Lifecycle Management (CLCM) in a data-driven approach. BIM has been used as a form of digital twin based on 3D models to improve productivity and reduce costs in the architecture, engineering, and construction (AEC) industries (Deng et al., 2021). The concept of digital twin aims to achieve synchronization of the real world with a virtual platform for seamless management and control of the construction process, facility management, and other life cycle processes in the built environment. Digital twins have the potential to predict undesirables and ensure desired performance of complex systems, including factories. The integration of BIM, Internet of Things (IoT), and data mining techniques has led to the development of a closed-loop digital twin framework for smart construction project management, enabling real-time data capture, modelling, analysis, and decision-making (Pan & Zhang, 2021). These advancements in virtual simulations and modelling technologies have the potential to enhance decision-making capabilities and improve the performance of construction projects throughout their life cycle.

#### 2.1.1 BIM is a subset of VSM

Building Information Modelling (BIM) stands as the cornerstone and subset of VSM, particularly in the architecture, engineering, and construction (AEC) sector as CLCM. BIM facilitates the coordination and optimization of MEP facilities, detects design incidents, and anticipates conflicts between disciplines (Dols et al., 2021) in CLCM domain. It goes beyond conventional 3D modelling, incorporating a comprehensive digital representation of structures enriched with data on materials, spatial relationships, costs, and more. This detailed information forms the bedrock for VSM, enabling stakeholders to conduct simulations and analyses on structural integrity, energy efficiency, and other critical factors. BIM's integration of diverse data facilitates spatial coordination, minimizing conflicts during construction.

#### 2.1.2 DT is a subset of VSM

DT stands as an intricately woven subset within the expansive landscape of virtual simulation and modelling. Emerging at the intersection of cutting-edge technologies, DT are sophisticated virtual replicas meticulously synchronized with physical objects or systems. This subset within the broader realm of VSM goes beyond traditional representations by dynamically incorporating real-time data (Biller et al., 2022). These twins mirror the intricate details and behaviours of their physical counterparts throughout their lifecycle in CLCM domain. While VSM technologies cover a diverse array of applications, DT, with their major focus on real-time integration and continuous synchronization, carve a specialized niche. They become indispensable tools, facilitating unparalleled insights, predictive analytics, and enhanced decision-making across CLCM industries, offering a dynamic bridge between the virtual and physical worlds.

### 2.2 Challenges of BIM & DT in CLCM

Integrating Building Information Modelling (BIM) and Digital Twin technologies in construction life cycle management presents challenges in handling unstructured cloud data, hindering effective utilization. The vast and unorganized nature of cloud data poses hurdles for BIM and Digital Twin applications. Extracting meaningful insights from this data requires advanced analytics techniques. Furthermore, IoT integration raises security and privacy concerns for real-time project monitoring. The dynamic nature of construction sites complicates real-time data synchronization, challenging the maintenance of accurate project information. Addressing these challenges is crucial for unlocking the full potential of BIM and Digital Twin technologies, enhancing construction life cycle management efficiency and decision-making processes.

## 3. METHODOLOGY

There is still no comprehensive understanding of the interaction between DT and BIM in construction projects in the repository of existing knowledge. In our study, we meticulously gathered a corpus of

100 articles from reputable databases such as Scopus, Google Scholar, and Web of Science. Our search was refined using targeted keywords including as "digital twin," "Building Information Modelling (BIM)," and "unstructured cloud data point," "construction life cycle management." The inclusion criteria focused on articles published within the last ten years to ensure currency and relevance. Following the initial collection, a meticulous screening process ensued, wherein articles not directly aligned with the core focus of our research were systematically excluded. After rigorous screening, we identified and selected a final set of 20 articles that hold direct relevance to our research objectives. This streamlined selection process ensures that our literature review is precisely tailored to investigate the intricate relationships between digital twin technology, Building Information Modelling (BIM), and the challenges associated with unstructured cloud data points in the context of construction life cycle management. The literature review process is illustrated in Figure 1.

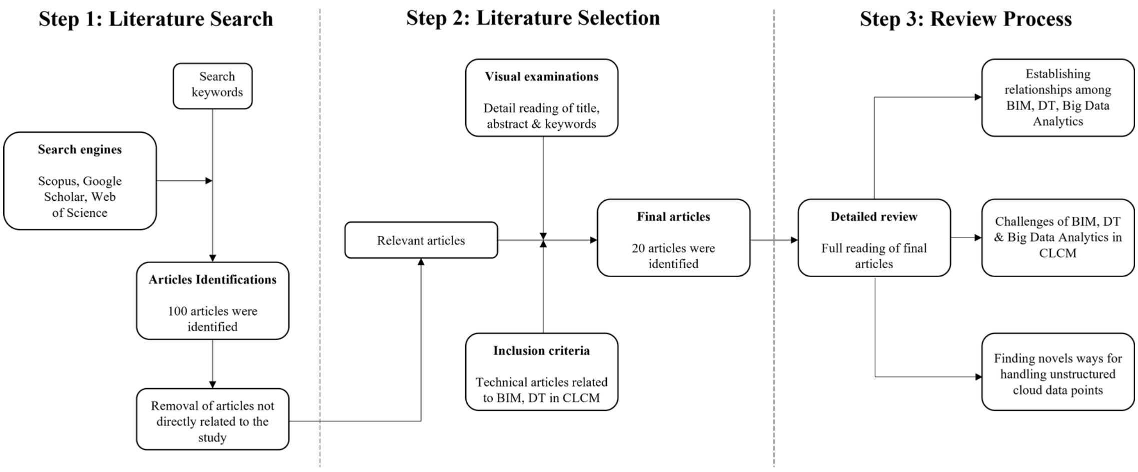


Figure 1: Overview of literature review process.

## 4. RESULTS & DISCUSSIONS

### 4.1 Distribution of articles by publication date

Based on our review process of 20 papers, the distribution plot in Figure 2 shows the temporal evolution of research in the fields of building information modelling (BIM) and digital twins. Publication dates are represented by the x-axis, which shows trends and concentrations over time. Plot peaks denote times of increased research effort and provide insights into how the focus on Digital Twin and BIM subjects is changing in both the academic and professional domains. With its thorough depiction of the research landscape, this visual representation is an invaluable tool for comprehending the relative significance and temporal dynamics of these two disciplines.

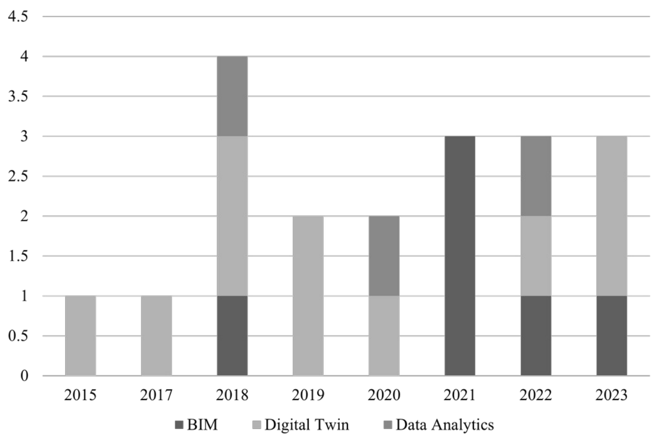


Figure 2: Distribution of articles by publishing year.

## 4.2 Distribution of articles by applied cases

The detailed, well-organized examination of each recognized BIM and DT use across the construction life cycle management process in different domains is summarized in Table 1 below. Given that most studies cover several BIM and DT uses and that these uses are closely interrelated, it is important to interpret the image accordingly. Consequently, an extensive number of articles are presented in numerous segments, with only a select few that stand out across all topics and are frequently cited below. table being described.

Table 1: List of articles analysed and domain covered for review process.

| No. | References | Domains cover from BIM & DT | | | | | |
|---|---|---|---|---|---|---|---|
| | | Prediction | Simulation | Monitoring | Lifecycle | Sensing | IoT |
| 1 | (Jedermann et al., 2023) | ✓ | ✓ | ✓ | | ✓ | ✓ |
| 2 | (Xia et al., 2023) | ✓ | ✓ | | | ✓ | ✓ |
| 3 | (Nguyen & Adhikari, 2023) | ✓ | ✓ | | | ✓ | ✓ |
| 4 | (Chandaluri & Nelakuditi, 2022) | ✓ | ✓ | ✓ | ✓ | | ✓ |
| 5 | (Lee et al., 2022) | ✓ | ✓ | ✓ | ✓ | ✓ | |
| 6 | (Biller et al., 2022) | ✓ | ✓ | | | ✓ | |
| 7 | (Dols et al., 2021) | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| 8 | (Pan & Zhang, 2021) | ✓ | ✓ | ✓ | | ✓ | ✓ |
| 9 | (Deng et al., 2021) | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| 10 | (Boje et al., 2020) | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| 11 | (Wang et al., 2020) | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| 12 | (Tomko & Winter, 2019) | ✓ | ✓ | ✓ | | ✓ | |
| 13 | (Zheng et al., 2019) | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| 14 | (Mohammadi & Taylor, 2018) | ✓ | ✓ | ✓ | ✓ | | ✓ |
| 15 | (DIng et al., 2018) | ✓ | ✓ | | | ✓ | ✓ |
| 16 | (Batty, 2018) | ✓ | ✓ | ✓ | | ✓ | ✓ |
| 17 | (Qi & Tao, 2018) | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| 18 | (Haag & Anderl, 2018) | ✓ | ✓ | | ✓ | ✓ | ✓ |
| 19 | (Schleich et al., 2017) | ✓ | ✓ | ✓ | | ✓ | |
| 20 | (Grieves, 2015) | ✓ | ✓ | | ✓ | ✓ | |

## 4.3 Interconnectivity & Big Data Analytics (BDA)

BIM serves as the core virtual framework that allows Digital Twin technology to dynamically integrate real-time data. Conversely, real-time data collection and sharing via IoT sensors is critical to improving digital twin and BIM environments. Big Data Analytics takes centre stage by analysing the enormous data sets from IoT, BIM, and Digital Twin and drawing perceptive conclusions. A thorough relationship between BIM, Digital Twin, IoT, and Big Data Analytics (BDA) is shown in Table 2, demonstrating how their cooperative efforts enhance Construction Life Cycle Management (CLCM). Along with streamlining data flow between IoT, BIM, Digital Twins, and Big Data Analytics, this interconnected relationship creates a strong basis for well-informed decision-making across the Construction Life Cycle. These technologies synergize for enhanced productivity, risk reduction, and innovation in construction and infrastructure management.

In alignment with (Grieves, 2015)'s approach, our review adopts a comprehensive perspective on the intricate interplay among DT, BIM, and BDA. This holistic view unfolds in three distinct dimensions (as shown in Figure 3): The physical components, the virtual models, and the connecting data. In the physical realm, Digital Twins embody real-world entities, mirroring their physical components, behaviours, and conditions. BIM serves as the digital counterpart, offering a detailed virtual representation of structures and systems.

Table 2: Comparisons among DT, BIM, IoT, and BDA.

| Features | DT | BIM | IoT | BDA |
|---|---|---|---|---|
| **Specific Purpose** | Virtual replica of a physical asset for real-time monitoring, optimization, and prediction. | Creating and managing information about a structure throughout its lifecycle (design, construction, operation). | Interconnecting devices and sensors to collect and exchange data wirelessly. | Analyzing large and complex datasets to extract patterns, trends, and insights. |
| **Key Features** | Dynamic virtual model, real-time data integration, simulation capabilities. | 3D modeling, parametric data, scheduling tools, clash detection, coordination features. | Sensor networks, data communication protocols, device interoperability standards. | Machine learning algorithms, statistical analysis, data visualization tools. |
| **Data Input** | Real-time sensor data, BIM models, historical data, external sources. | Architectural plans, engineering data, construction specifications, material properties. | Sensor data from various devices (temperature, pressure, energy consumption, etc.). | All data sources from digital twins, BIM models, IoT sensors, external databases. |
| **Data Output** | Visualizations, alerts, reports, predictions, optimization scenarios. | Drawings, schedules, cost estimates, clash reports, 3D models with integrated information. | Sensor readings, device statuses, environmental data, real-time alerts. | Predictive models, performance reports, optimization recommendations, anomaly detection, risk assessments. |
| **Benefits** | Improved efficiency, reduced downtime, data-driven decision making, predictive maintenance. | Improved design accuracy, reduced construction errors, better project coordination, optimized resource allocation. | Increased automation, remote control, real-time insights, improved asset tracking, data-driven decisions. | Improved decision making, resource optimization, risk mitigation, proactive maintenance, discovery of hidden insights. |

The synergy between Digital Twins and BIM forms a bridge between the physical and virtual, enhancing understanding and decision-making. Big Data Analytics acts as the connective tissue, leveraging vast datasets generated by Digital Twins and BIM to derive meaningful insights. This triad of physical, virtual, and data-driven elements creates a symbiotic relationship, empowering a transformative understanding of complex systems and fostering innovation in diverse domains.

The Physical-Virtual-Data interconnectivity, which is one of the many recurrent ideas in our extensive literature review, is defined and segmented in Table 3, with each component being viewed as a feature or ability. The interchange of Data in different forms facilitates the interaction between the Virtual-Physical duality. According to Grieves, data flows from the Physical to the Virtual are different and require processing. On the other hand, data passes through a series of changes that result in processed information and knowledge that is stored in digital models and given additional context. Actuators subsequently provide the Physical with this updated knowledge. As a result, the Virtual section uses the insights gained from processing real-world data that the Physical segment gathers to inform day-to-day decisions about the Physical. This linked loop demonstrates the mutually beneficial interplay between real-world objects, digital representations, and the transformational potential of data-driven insights.

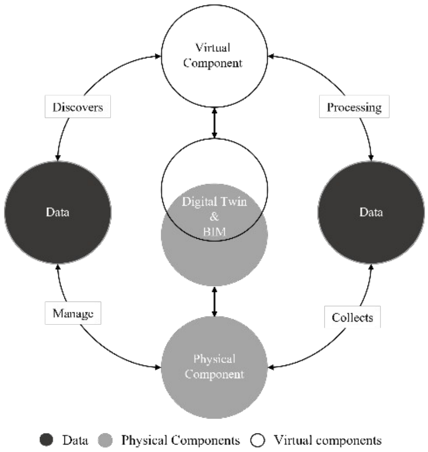


Figure 3: Physical-virtual-data interconnectivity.

Table 3: Ability of Physical-virtual-data paradigm and their description.

| Components | Ability | Descriptions |
|---|---|---|
| The Physical | Sensing | Real-time sensor-based observation of the physical world. |
| | Monitoring | Capacity to monitor, notify, and issue alerts regarding pertinent physical changes. |
| | Accuracy | Capacity to alter, activate, or deactivate physical elements in response to virtual choices. |
| The Virtual | Simulation | Application of engineering simulation models from different domains of application. |
| | Prediction | Capacity to forecast physical behavior using digital simulations and sensing. |
| | Optimization | The aptitude for utilizing optimization techniques and suggesting astute resource distribution in real time. |
| The Data | IoT | Capacity to combine and exchange data transmitted by IoT gadgets. |
| | Data Linking | Capacity to use Semantic Web protocols for data integration and sharing. |
| | Storing | Capability of reasoning, supporting rules, and storing system facts |

### 4.3.1 The Physical Components

Building Information Modelling (BIM) and Digital Twins (DT) rely on a range of physical components for robust data acquisition and effective integration of the physical and virtual domains. Advanced sensors, electronic elements, and machine vision systems like IoT devices play pivotal roles in capturing real-time mechanical data, surpassing traditional methods like programmable logic control (Li et al., 2021). The Sensors, including RFID for asset tracking and motion sensors for occupancy data, alongside electronic components, contribute to constructing detailed digital twins (Liu et al., 2023). Photogrammetry enhances accuracy by capturing spatial information for intricate 3D models. Laser scanners ensure precise geometric data, elevating structural accuracy, while smart meters track energy consumption, fostering sustainable designs. These seamlessly integrated components form the robust foundation of BIM and Digital Twins, advancing intelligent infrastructure development. Moreover, the convergence of edge computing accelerates data processing in BIM and Digital Twins, while AI algorithms enable predictive maintenance and performance optimization. This synergy promises to drive innovation, fostering smarter and more sustainable urban development.

#### 4.3.2 The Virtual Components

The virtual components of BIM and DT intricately weave together to create a dynamic and comprehensive representation of physical assets. In BIM, digital models act as the essential, faithfully reproducing architectural, structural, and system intricacies within a virtual space. Augmented by databases rich in material details, specifications, and maintenance records, BIM enables robust simulations for scenario testing and performance analysis. DT elevates these digital models from BIM by establishing a real-time link with the physical asset (Heuser et al., 2022). This dynamic virtual counterpart mirrors the present state of the physical entity, amalgamating data from sensors, IoT devices, and diverse sources. This connection allows for continuous monitoring, analysis, and optimization. Throughout the construction life cycle, from design inception to ongoing operations, these interconnected virtual elements streamline collaboration, boost efficiency, and champion sustainability by presenting a unified and evolving representation of the physical asset.

#### 4.3.3 The Data

Data is the component which leverages and bridges both physical and virtual components. When it comes to decision-making and implication of DT & BIM, data fusion is essential since it improves prediction and system optimization through connecting data. In the management of construction life cycles, the essence of BIM and DT lies not solely in physical components and virtual models but predominantly in data fusion. Data fusion acts as the linchpin, amalgamating information from sensors, BIM models, and real-time inputs within DT. This comprehensive integration enhances precision, augments contextual comprehension, and fosters data-driven decision-making throughout the construction lifecycle.

(Lee et al., 2022) presented a reconfigurable module with three fusion layers at the data, feature, and decision levels for multi-sensor data fusion. The decision layer uses present equations to ease final decision-making, while the feature layer sets up a fusion tree and the data layer refines the raw data. In a similar vein, (Hijji et al., 2023) introduced an intelligent hierarchical structure that makes use of mobile edge AI training, DL methods, and 6G connectivity technologies. In order to detect potholes, the suggested framework combines data level fusion with the convolution neural network (CNN) model, which combines sensory and visual input. As an alternative, a decision-level data fusion model framework was presented by (Wei et al., 2020) to enhance prediction performance in predictive maintenance and quality control. The suggested framework formulates the integration as a convex optimization problem, converting low-dimensional decisions from individual sensor data, such as temperature and vibration, into high-dimensional ones. The method is applied in two scenarios: (1) aircraft engine predictive maintenance, where it estimates remaining usable life; and (2) quality control in additive manufacturing, where it forecasts surface roughness.

### 4.4 Data Fusion Challenges

Five primary data fusion challenges in construction management are highlighted in Figure 4, which summarizes insights from 20 articles. As a visual aid, it illuminates the complex challenges associated with integrating disparate datasets in the construction industry.

Harmonizing unstructured cloud data points formidable challenges in data fusion, stemming from issues like disparate formats and variable data quality. Achieving cohesion amidst diverse cloud data points demands robust strategies to navigate complexities and ensure meaningful integration from diverse sources like sensors and photogrammetry. Identical to ontological and semantic analysis, which also has 5 instances, these approaches highlight the challenges of preserving and interpreting the structure and semantic characteristics of data in order to preserve its profound meaning. The four instances of resource and computational constraints deal with the difficulties associated with constrained computational resources, especially when handling large data sets and choosing, putting into practice, and verifying suitable algorithms.

The final section, Pragmatism and Real-World Application, discusses the discrepancy between theoretical knowledge and its application in the real world and the validity of actual data through three examples. The difficulties of applying theoretical and conceptual knowledge in practical situations are also highlighted by this theme, particularly for data fusion-based DT applications in the infrastructure management field.

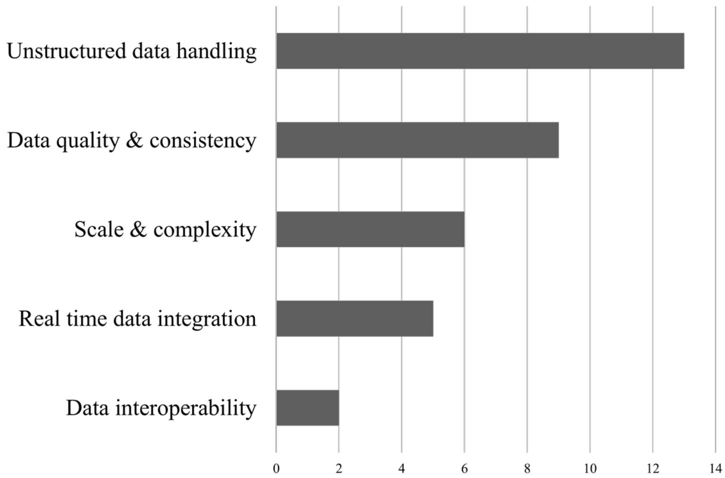


Figure 4: Challenges of data fusion process and their occurrences in review articles.

### 4.4.1 Handling unstructured cloud data points

Structured and unstructured data are intertwined in CLCM after acquisition from various medium, and managing unstructured cloud data points for BIM and digital twins presents new challenges. Because unstructured data comes in a multitude of formats, with missing points, varying quality, and requiring specialized processing to extract meaningful insights throughout the entire life cycle of construction projects, managing this wealth of data demands careful strategies. The five-step process illustrated in Figure 5 provides a strategic approach to managing unstructured cloud data points by (Wang et al., 2020)'s approach. The first phase, Data Cleansing, entails the careful elimination of errors and inconsistencies to guarantee the accuracy of the data. Data Registration then streamlines accessibility and retrieval by cataloguing and organizing the cleaned data. After organization, data segmentation divides the data into digestible chunks to enable focused analysis. In order to improve comprehension and interpretation, the fourth step, Object Recognition, uses sophisticated algorithms to recognize and categorize objects within the divided data. When taken as a whole, these actions enable the effective use of unstructured cloud data in construction life cycle management. Throughout the construction life cycle, segmentation allows for focused analysis, object recognition improves comprehension, registration helps with organization, and data cleansing assures accuracy. All of these factors support well-informed decision-making and efficient procedures.

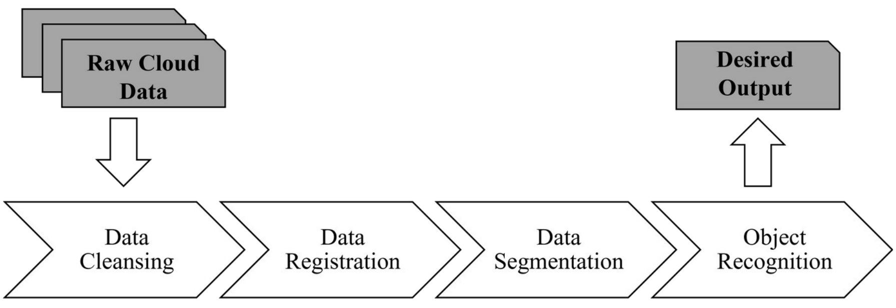


Figure 5: Process of handling unstructured cloud data points.

Beyond the initial stages of cleansing and registration, data segmentation ensures a nuanced analysis, while object recognition employs advanced algorithms for precise categorization, collectively facilitating the effective utilization of unstructured cloud data in construction life cycle management. In essence, these steps synergize to bolster decision-making processes and streamline procedures, demonstrating the indispensable role of data management in the modern construction landscape. Additionally, the methodical dissection shown in Table 4, which is consistent with the approaches of (Wang et al., 2020), makes it easier to comprehend the complexities of handling unstructured cloud data during the course of the building process. This extensive manual not only helps researchers and practitioners through each step but also emphasizes how important it is from a strategic standpoint to handle data acquisition, cleaning, segmentation, and object recognition well. This methodical approach is essential for maximizing operational effectiveness and decision-making as the sector embraces digital transformation.

Table 4: Different approaches for handling unstructured cloud data points.

| Data acquisition | Data Cleansing | Data Segmentation | Object Recognition |
|---|---|---|---|
| 3D Laser Scanning | Removing Mixed Pixels | Clustering-Based | Geometric Shape Descriptor |
| Photogrammetry | Removing Speckle | Edge-Based | Hard-Coded Knowledge |
| Videogrammetry | Removing Wrap-Around Noise | Region-Based | Supervised Learning |
| RGB-D Camera | Noise Smoothing | Graph-Based | BIM-Vs.-Scan |
| Stereo Camera | Removing Inconsistency Among Scans | Hybrid | Deep Learning |

## 5. CONCLUSIONS

The convergence of real-world applications with virtual simulations, driven by the Internet of Things (IoT), stands as a transformative force in the construction industry. The deployment of Digital Twin (DT) technology, which integrates real-time sensor data into virtual models, is identified as a pivotal driver for advancing Construction Life Cycle Management (CLCM). Throughout this research, the integration of Building Information Modelling (BIM) as the foundational virtual framework, coupled with Digital Twin technology, has been explored to enhance efficiency, safety, and sustainability in construction projects. The study recognizes the significance of Virtual Simulations & Modelling (VSM), facilitated by BIM, and the added value brought by Digital Twin technology in dynamically incorporating real-time data. However, the integration of unstructured cloud data poses challenges in real-time data synchronization and harmonization. Efficient data acquisition, especially from diverse sources, is crucial for maintaining accuracy and responsiveness in the BIM-digital twin system.

The study has undertaken a thorough literature review to extract insights from existing solutions. By understanding interconnectivity principles highlighted in the literature, the study guides the development of standardized protocols, fostering seamless integration and ensuring a coherent flow of real-time data across BIM, digital twins, and diverse cloud-based sources. In addition to synthesizing knowledge on the interaction of IoT, big data analytics, BIM, and DT applications in CLCM, this study addresses challenges in data fusion. The review identifies innovative methods for data acquisition, registration, cleansing, segmentation, and object recognition, specifically handling unstructured point cloud data.

The outcomes of this research contribute to a comprehensive knowledge base, empowering stakeholders in the construction industry to make informed decisions. As technological breakthroughs continue to transform the sector, the study provides a roadmap for effectively navigating challenges in data integration and fostering the adoption of advanced technologies. Moving forward, the insights gained from this research will play a crucial role in shaping the future of construction research, where efficiency, safety, and sustainability are elevated through the seamless integration of real-world and virtual elements.

## REFERENCES

Abo-Khalil, A. G. (2023). Digital twin real-time hybrid simulation platform for power system stability. Case Studies in Thermal Engineering, 49, 103237–103237. https://doi.org/10.1016/J.CSITE.2023.103237.

Batty, M. (2018). Digital twins. Https://Doi.Org/10.1177/2399808318796416, 45(5), 817–820. https://doi.org/10.1177/2399808318796416.

Biller, B., Jiang, X., Yi, J., Venditti, P., & Biller, S. (2022). Simulation: The Critical Technology in Digital Twin Development. Proceedings - Winter Simulation Conference, 2022-December, 1340–1355. https://doi.org/10.1109/WSC57314.2022.10015246.

Boje, C., Guerriero, A., Kubicki, S., & Rezgui, Y. (2020). Towards a semantic Construction Digital Twin: Directions for future research. In Automation in Construction (Vol. 114). Elsevier B.V. https://doi.org/10.1016/j.autcon.2020.103179.

Chandaluri, R., & Nelakuditi, U. (2022). Monograph on Components, Design, and Applications of Digital Twin. International Journal of Next-Generation Computing. https://doi.org/10.47164/IJNGC.V13I3.768.

Deng, M., Menassa, C. C., & Kamat, V. R. (2021). From BIM to digital twins: a systematic review of the evolution of intelligent building representations in the AEC-FM industry. Journal of Information Technology in Construction, 26(5), 58–83. https://doi.org/10.36680/J.ITCON.2021.005.

DIng, K., Shi, H., Hui, J., Liu, Y., Zhu, B., Zhang, F., & Cao, W. (2018). Smart steel bridge construction enabled by BIM and Internet of Things in industry 4.0: A framework. ICNSC 2018 - 15th IEEE International Conference on Networking, Sensing and Control, 1–5. https://doi.org/10.1109/ICNSC.2018.8361339.

Dols, J. F., Molina, J., Camacho-Torregrosa, F. J., Llopis-Castelló, D., & García, A. (2021). Development of driving simulation scenarios based on building information modeling (BIM) for road safety analysis. Sustainability (Switzerland), 13(4), 1–22. https://doi.org/10.3390/su13042039.

Dosumu, O. S., Mahame, C., Niyitegeka, S., & Hahiirwuwambaza, J. A. (2023). Application and Challenges of Adopting Internet of Things (IOT) in the Rwandan Construction Industry. Journal of Construction in Developing Countries, 28(2), 1–22. https://doi.org/10.21315/JCDC-05-22-0098.

Ferrigno, E., & Barsola, G. A. (2023). 3D Real Time Digital Twin. SPE Latin American and Caribbean Petroleum Engineering Conference Proceedings, 2023-June. https://doi.org/10.2118/213115-MS.

Grieves, M. (2015). Digital Twin: Manufacturing Excellence through Virtual Factory Replication.

Haag, S., & Anderl, R. (2018). Digital twin – Proof of concept. Manufacturing Letters, 15, 64–66. https://doi.org/10.1016/j.mfglet.2018.02.006.

Heuser, S., Guevara Cano, L. A., Eyrich, W., & Pizarro, F. (2022). Digital Twin, Simulation BIM and Virtual Reality Models for Substation Lifecycle in Engineering, Operation, Asset Management & Maintenance. 2022 IEEE PES Generation, Transmission and Distribution Conference and Exposition - Latin America, IEEE PES GTD Latin America 2022. https://doi.org/10.1109/IEEEPESGTDLATINAMERI53482.2022.10038293.

Hijji, M., Iqbal, R., Kumar Pandey, A., Doctor, F., Karyotis, C., Rajeh, W., Alshehri, A., & Aradah, F. (2023). 6G Connected Vehicle Framework to Support Intelligent Road Maintenance Using Deep Learning Data Fusion. IEEE Transactions on Intelligent Transportation Systems, 24(7), 7726–7735. https://doi.org/10.1109/TITS.2023.3235151.

Jedermann, R., Singh, K., Lang, W., & Mahajan, P. (2023). Digital twin concepts for linking live sensor data with real-time models. Journal of Sensors and Sensor Systems, 12(1), 111–121. https://doi.org/10.5194/JSSS-12-111-2023.

Jia, Y., Hosseini, M. R., Zhang, B., Martek, I., Nikmehr, B., & Wang, J. (2022). A scientometric-content analysis of integration of BIM and IoT. IOP Conference Series, 1101(7), 072002–072002. https://doi.org/10.1088/1755-1315/1101/7/072002.

Lee, S. K., Hong, S. H., Jun, W. H., & Hong, Y. S. (2022). Multi-Sensor Data Fusion with a Reconfigurable Module and Its Application to Unmanned Storage Boxes. Sensors, 22(14). https://doi.org/10.3390/s22145388.

Li, H., Liu, G., Wang, H., Wen, X., Xie, G., Luo, G., Zhang, S., & Yang, M. (2021). Mechanical movement data acquisition method based on the multilayer neural networks and machine vision in a digital twin environment. Digital Twin, 1, 6. https://doi.org/10.12688/DIGITALTWIN.17441.1.

Liu, X., Jiang, D., Tao, B., Xiang, F., Jiang, G., Sun, Y., Kong, J., & Li, G. (2023). A systematic review of digital twin about physical entities, virtual models, twin data, and applications. Advanced Engineering Informatics, 55, 101876. https://doi.org/10.1016/J.AEI.2023.101876.

Madubuike, O. C., Anumba, C. J., & Agapaki, E. (2023). Scenarios for digital twin deployment in healthcare facilities management. Journal of Facilities Management. https://doi.org/10.1108/JFM-10-2022-0107.

Mohammadi, N., & Taylor, J. E. (2018). Smart city digital twins. 2017 IEEE Symposium Series on Computational Intelligence, SSCI 2017 - Proceedings, 2018-January, 1–5. https://doi.org/10.1109/SSCI.2017.8285439.

Nguyen, T. D., & Adhikari, S. (2023). The Role of BIM in Integrating Digital Twin in Building Construction: A Literature Review. Sustainability 2023, Vol. 15, Page 10462, 15(13), 10462. https://doi.org/10.3390/SU151310462.

Pan, Y., & Zhang, L. (2021). A BIM-data mining integrated digital twin framework for advanced project management. Automation in Construction, 124, 103564. https://doi.org/10.1016/j.autcon.2021.103564.

Qi, Q., & Tao, F. (2018). Digital Twin and Big Data Towards Smart Manufacturing and Industry 4.0: 360 Degree Comparison. IEEE Access, 6, 3585–3593. https://doi.org/10.1109/ACCESS.2018.2793265.

Raj, N. (2023). Analysis of Fog Computing: An Integrated Internet of Things (IoT) Fog Cloud Infrastructure for Big Data Analytics and Cyber Security. 2023 International Conference on Artificial Intelligence and Smart Communication, AISC 2023, 1215–1219. https://doi.org/10.1109/AISC56616.2023.10085681.

Santos, R. S. dos, & Assayag, E. S. (2022). INTERNET OF THINGS (IOT) APPLIED IN CONSTRUCTION INDUSTRY: A SYSTEMATIC REVIEW. International Journal of Engineering Technologies and Management Research, 9(12), 23-29–23–29. https://doi.org/10.29121/IJETMR.V9.I12.2022.1272.

Schleich, B., Anwer, N., Mathieu, L., & Wartzack, S. (2017). Shaping the digital twin for design and production engineering. CIRP Annals - Manufacturing Technology, 66(1), 141–144. https://doi.org/10.1016/j.cirp.2017.04.040.

Tomko, M., & Winter, S. (2019). Beyond digital twins – A commentary. Environment and Planning B: Urban Analytics and City Science, 46(2), 395–399. https://doi.org/10.1177/2399808318816992/ASSET/2399808318816992.FP.PNG_V03.

Wang, Q., Tan, Y., & Mei, Z. (2020). Computational Methods of Acquisition and Processing of 3D Point Cloud Data for Construction Applications. Archives of Computational Methods in Engineering, 27(2), 479–499. https://doi.org/10.1007/s11831-019-09320-4.

Wei, Y., Wu, D., & Terpenny, J. (2020). Decision-Level Data Fusion in Quality Control and Predictive Maintenance. IEEE Transactions on Automation Science and Engineering, 18(1), 184–194. https://doi.org/10.1109/TASE.2020.2964998.

Xia, D., Shi, J., Wan, K., Wan, J., Martinez-Garcia, M., & Guan, X. (2023). Digital Twin and Artificial Intelligence for Intelligent Planning and Energy-Efficient Deployment of 6G Networks in Smart Factories. IEEE Wireless Communications, 30(3), 171–179. https://doi.org/10.1109/MWC.017.2200495.

Zheng, Y., Yang, S., & Cheng, H. (2019). An application framework of digital twin and its case study. Journal of Ambient Intelligence and Humanized Computing, 10(3), 1141–1153. https://doi.org/10.1007/S12652-018-0911-3/METRICS.