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Integration of Blockchain and Digital Twin for Smart Asset Lifecycle Management

SMART BUILT ENVIRONMENT

Integration of Blockchain and Digital Twin for Smart Asset Lifecycle Management

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Med stöd från

VINNOVA Sveriges innovationsmyndighet

Energimyndigheten

FORMAS

Strategiska innovations-program

Förord

Smart Built Environment är ett strategiskt innovationsprogram för hur samhälls-byggnadssektorn kan bidra till Sveriges resa mot att bli ett globalt föregångsland som realiserar de nya möjligheter som digitaliseringen för med sig. Smart Built Environment är ett av 17 strategiska innovationsprogram som har fått stöd inom ramen för Strategiska innovationsområden, en gemensam satsning mellan Vinnova, Energimyndigheten och Formas. Syftet med satsningen är att skapa förutsättningar för Sveriges internationella konkurrenskraft och bidra till hållbara lösningar på globala samhällsutmaningar.

Samhällsbyggnadssektorn är Sveriges enskilt största sektor som påverkar hela vår be-byggda miljö, men den är fragmenterad med många aktörer och processer. Att förändra samhällsbyggandet med digitaliseringen som drivkraft kräver därför samverkan mellan många olika aktörer. Smart Built Environment tar ett samlat grepp över de möjligheter som digitaliseringen innebär och blir en katalysator för spridningen av nya möjligheter och affärsmodeller.

Programmets mål är att till 2030 uppnå:

- 40 % minskad miljöpåverkan i ett livscykelperspektiv för nybyggnad och renovering
- 33 % minskning av total tid från planering till färdigställande för nybyggnad och renovering
- 33 % minskning av de totala byggkostnaderna
- flera nya värdekedjor och affärsmodeller baserade på livscykelperspektiv, plattformar samt nya konstellationer av aktörer

I programmet samverkar programparter från näringsliv, kommuner, myndigheter, bransch- och intresseorganisationer, institut och akademi. Tillsammans nyttiggör vi den kunskap som tas fram i programmet.

Integrering av blockkedjor och digitala tvillingar är ett av de projekt som har genomförts inom programmet. Det har letts av Ibrahim Yitmen och har genomförts i samarbete med både industriella partners Pyhtagoras AB och Plan B AB samt akademiska partners University of Turin, TU Wien och University of Nottingham.

Projektet undersökte integrationen av framväxande tekniker som digitala tvillingar, blockkedjor och artificiell intelligens med tillgångshanteringsprocesser i den smarta byggda miljön för att säkerställa säker och tillgänglig databehandling.

Arbetet har inkluderat utvecklingen av en blockchainaktiverad prototyp för en digital tvillingplattform för att förverkliga den fulla potentialen av smart tillgångslivscykelhantering i det digitala ekosystemet, vilket resulterar i säkra, transparenta, spårbara och informationsrika digitala tvillingapplikationer och rapportverktyg.

Jönköping, 11 Augusti 2025

Sammanfattning

Det ökande fokuset på hållbarhet bland hyresgäster och andra intressenter driver utvecklingen från traditionell Anläggningsförvaltning mot Livscykelhantering för tillgångar, med ett starkare fokus på drift och underhåll. Trots denna utveckling står tillgångsförvaltningssektorn fortfarande inför betydande utmaningar, såsom fragmenterade processer, komplexa leveranskedjor och bristande integration mellan olika faser i fastigheters livscykel. För att möta dessa utmaningar integreras framväxande digitala teknologier såsom Digitala Tvillingar, Artificiell Intelligens, Sakernas Internet **o**ch Blockchain i branschstandardiserade BIM-baserade leveranskedjor för anläggningsförvaltning för att skapa sömlösa kopplingar mellan arbetsprocesser, intressenter och tillgångarnas livscykelfaser.

Detta arbete har lett till utvecklingen av en blockchainaktiverad Digitala Tvillingar **-** plattformsprototyp, utformad för att frigöra den fulla potentialen hos smart Livscykelhantering för tillgångar inom ett digitalt ekosystem. Plattformen möjliggör säkra, transparenta, spårbara och informationsrika Digital Twin-tillämpningar samtidigt som den erbjuder avancerade funktioner för rapportering och beslutsstöd. Genom att kombinera Digital Twin-teknologi med ett distribuerat blockkedjebaserat system för informationslagring möjliggör den samverkande plattformen en omfattande integration, analys och hantering av tillgångsdata genom hela tillgångens livscykel.

Vidare möjliggör plattformen prediktiv analys av tillgångars beteende och prestanda i byggnadsanläggningar, stödjer intelligenta styrsystem för byggnader och tillhandahåller avancerade verktyg för välgrundat beslutsfattande inom drift- och underhållsverksamhet. Den integrerade tekniken bidrar till att uppnå hållbarhetsmål genom att förbättra den operativa effektiviteten, minska mänskliga fel, minimera driftstopp och sänka administrativa kostnader. Projektet bidrar dessutom till att öka medvetenheten och stärka kunskapen inom Anläggningsförvaltning, fastighetssektorn och den offentliga sektorn, inklusive kommuner och andra offentliga organisationer, och främjar därmed införandet av digitala teknologier för hållbar och intelligent tillgångsförvaltning.

Summary

The growing emphasis on sustainability among tenants and stakeholders is driving the transition of traditional facility management (FM) toward Asset Life Cycle Management (ALM), with a stronger focus on operation and maintenance (O&M). Despite this shift, the asset management sector continues to face significant challenges, including fragmented processes, complex supply chains, and disconnected phases across the real estate asset life cycle. To address these challenges, emerging digital technologies such as Digital Twins (DTs), Artificial Intelligence (AI), the Internet of Things (IoT), and Blockchain are being integrated into industry-compliant Building Information Modelling (BIM)-based FM supply chains to establish seamless connections among work processes, stakeholders, and asset life cycle phases.

This work has led to the development of a Blockchain-enabled Digital Twin platform prototype designed to unlock the full potential of smart Asset Life Cycle Management within a digital ecosystem. The platform supports secure, transparent, traceable, and information-rich Digital Twin applications while providing advanced reporting and decision-support capabilities. By combining Digital Twin technology with a distributed blockchain record-keeping system, the collaborative platform enables comprehensive asset data integration, analysis, and management throughout the asset life cycle.

Furthermore, the platform facilitates predictive analysis of asset behaviour and performance in building facilities, supports intelligent building control systems, and provides advanced tools for informed decision-making across operation and maintenance activities. The integrated technology contributes to achieving sustainability objectives by improving operational efficiency, reducing human error, minimizing system downtime, and lowering administrative costs. In addition, the project enhances awareness and strengthens knowledge within the facility management, real estate, and public sectors, including municipalities and other public organizations, thereby promoting the adoption of digital technologies for sustainable and smart asset management.

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1 INTRODUCTION

1.1 Theoretical Background

In asset-centric organizations, such as real estate and Asset Management (AM) companies, effective asset management is essential for maximizing asset value and realizing their full operational potential (Heaton et al., 2019; Muller et al., 2019; Munir et al., 2020; Tchana et al., 2019). One of the primary challenges is identifying, organizing, and maintaining the information required to manage assets efficiently throughout their entire life cycle (Heaton, 2020). To address this need, ISO 19650-1 (ISO, 2018) introduces the concept of Asset Information Models (AIMs), which provide structured repositories of information required for asset management. The content of an AIM is defined by Asset Information Requirements (AIR), which are derived from Organizational Information Requirements (OIR), ensuring that asset information aligns with organizational objectives.

Although existing asset management systems can capture and store asset-related information, they often face limitations in data integration, interoperability, and the management of dynamic, real-time information (Heaton, 2020; Lu et al., 2020b). Digital Twins (DTs) have emerged as a promising solution by enabling continuously updated, reliable, and data-rich virtual representations of physical assets throughout their life cycle (Dietz and Pernul, 2020; Götz et al., 2022; Jiang et al., 2021; Lee et al., 2021; Lu et al., 2020a; Macchi et al., 2018; Opoku et al., 2021; Shahzad et al., 2022; Yitmen et al., 2021; Zhao et al., 2022a). Within the Architecture, Engineering, Construction, Operation, and Facility Management (AECO-FM) industry, Digital Twins are increasingly being adopted to leverage Artificial Intelligence (AI) and Machine Learning (ML) for monitoring, analyzing, and predicting asset performance, thereby improving operational efficiency, supporting predictive maintenance, and reducing operational costs (Macchi et al., 2018; Ozturk, 2021; Zhao et al., 2022b).

Nevertheless, the effectiveness of Digital Twins depends on the reliability, integrity, and security of the underlying data. In this context, Blockchain Technology (BCT) provides a robust foundation by enabling a decentralized and immutable distributed ledger that ensures secure data exchange, preserves data integrity, and coordinates trusted Digital Twin environments. The integration of Blockchain with Digital Twins enhances transparency, traceability, and trust across asset management processes, thereby supporting more secure, collaborative, and intelligent decision-making throughout the asset life cycle (Lee et al., 2021; Rasheed et al., 2020; Suhail et al., 2022; Teisserenc and Sepasgozar, 2021a).

1.1.1 Information Management in the Asset Management Process

Asset Management (AM) has become increasingly important in both research and industry as a means of maximizing the value of physical assets throughout their entire life cycle (Macchi et al., 2018). According to the ISO 55000 series (ISO, 2014), AM comprises coordinated activities undertaken by an organization to realize value from its assets through systematic policies, objectives, and management processes. Complementing this

perspective, ISO 19650-1 (ISO, 2018) provides a standardized framework for managing asset information across the building life cycle through the development of an Asset Information Model (AIM). The AIM serves as a centralized repository that stores both structured data, such as databases, schedules, and 3D BIM models, and unstructured data, including documents, images, videos, and audio recordings, to support informed decision-making throughout the asset life cycle (Hellenborn et al., 2024).

The content of an AIM is defined by Asset Information Requirements (AIR), which are derived from Organizational Information Requirements (OIR). The OIR specifies the information required to achieve an organization's strategic objectives and asset management goals, ensuring that the AIM supports effective decision-making across operation and maintenance (O&M) and other life-cycle phases. Consequently, the alignment between OIR, AIR, and the AIM is fundamental for achieving efficient and value-driven asset management.

Despite the increasing adoption of Building Information Modeling (BIM) in asset management, the Architecture, Engineering, Construction, Operation, and Facility Management (AECO-FM) industry continues to face significant challenges related to project complexity, fragmented information, inconsistent data standards, and limited interoperability across digital platforms (Heaton, 2020; Shahzad et al., 2022a,b). A major challenge for asset-centric organizations is determining which information should be collected, structured, and maintained to support effective asset management throughout the asset life cycle. Misalignment between organizational objectives, OIR, AIR, and the resulting AIM frequently leads to incomplete or inconsistent information, limiting the ability of organizations to optimize asset performance and maximize long-term value.

Although several standards promote the integration of BIM data into the operation and maintenance phase and recommend the development of Asset Information Models, comprehensive frameworks that integrate strategic, process, and technical standards remain limited (Heaton, 2020). In particular, the standardization and semantic structuring of AIM data are critical for ensuring data consistency, interoperability, and long-term maintainability. An ontology-based data structure offers an effective approach for establishing semantic interoperability and enabling seamless integration between Asset Information Models and Digital Twin (DT) platforms. However, the manual development, maintenance, and continuous updating of such ontologies remain labor-intensive and difficult to scale, highlighting the need for more intelligent and automated approaches to managing asset information (Yitmen et al., 2023).

1.1.2 Digital Asset Management Tools

Within the Asset Management (AM) process, effective decision-making depends on access to real-time information on asset performance, reliable communication among stakeholders, and secure, trustworthy records of historical real estate data (Lu et al., 2019, 2020b; Macchi et al., 2018). Achieving these objectives requires high levels of data interoperability, validity, integrity, and traceability across the asset life cycle. At the same time, AM organizations face growing pressure to enhance asset performance and service quality despite constrained financial resources, while complying with regulatory requirements, fulfilling social responsibilities, and minimizing environmental impacts. These challenges have accelerated the adoption of advanced digital technologies to support

more intelligent and data-driven asset management practices (Heaton, 2020; Heaton and Parlikad, 2020).

The widespread implementation of Building Information Modeling (BIM) within the Architecture, Engineering, Construction, Operation, and Facility Management (AECO-FM) industry has facilitated the increasing use of BIM-based approaches for Asset Management (Alnaggar and Pitt, 2019; Heaton, 2020; Heaton and Parlikad, 2020). Although BIM has demonstrated substantial benefits during the design and construction phases, its application in Operation and Maintenance (O&M) remains relatively limited. Traditional BIM models often lack the dynamic data integration, real-time connectivity, advanced analytics, and decision-support capabilities required to address the complexity of O&M activities (Boje et al., 2020; Lu et al., 2019; Shahzad et al., 2022).

Consequently, there is a growing need for an integrated digital platform capable of managing and synchronizing information across distributed databases and heterogeneous information systems. Such a platform can facilitate seamless data exchange, improve interoperability, and support comprehensive Operation and Maintenance activities through continuous monitoring, predictive analysis, and informed decision-making, thereby enhancing the overall effectiveness and sustainability of asset management throughout the asset life cycle (Lu et al., 2021).

1.1.3 Digital Twins and Artificial Intelligence

Digital Twins (DTs) provide advanced decision-support capabilities for Asset Management (AM) by delivering reliable, real-time information throughout an asset's entire life cycle (Yitmen et al., 2021; Shahzad et al., 2022; Zhao et al., 2022a,b). A Digital Twin is a high-fidelity virtual representation of a physical asset that enables continuous bidirectional data exchange, allowing both real-time monitoring and operational control (Ozturk, 2021; Shahzad et al., 2022). Unlike Building Information Modeling (BIM), which primarily represents static building information, Digital Twins integrate both static data, such as design and construction information, and dynamic data, including real-time operational conditions, sensor measurements, and performance indicators, into a unified digital environment capable of generating actionable insights for asset management (Heaton and Parlikad, 2020).

The capabilities of Digital Twins are further strengthened through the integration of Internet of Things (IoT) sensors, which continuously collect real-time data from physical assets and provide the foundation for Artificial Intelligence (AI) and Machine Learning (ML) models to perform predictive analytics, anomaly detection, and performance optimization (Lukesh et al., 2021). The evolution of Digital Twin technology has progressed through three generations: (1) sensing and monitoring Digital Twins, which focus on real-time data acquisition; (2) AI-enabled Digital Twins, which incorporate data analytics and predictive capabilities; and (3) semantic cognitive Digital Twins, which integrate advanced AI techniques, including deep learning and semantic reasoning, to support autonomous and intelligent decision-making (Yitmen et al., 2021).

By combining real-time monitoring with predictive analytics, Digital Twins enable organizations to anticipate changes in asset condition, optimize maintenance strategies, and improve the operational performance and resilience of buildings (Ozturk et al., 2021). Although Machine Learning has significant potential to optimize operational decision-making, reduce maintenance costs, and improve efficiency, its adoption within the Architecture, Engineering, Construction, Operation, and Facility Management (AECO-FM) industry remains constrained by challenges such as insufficient high-quality structured data, fragmented information sources, limited interoperability, and high implementation costs (Bouabdallaoui et al., 2021; Pan and Zhang, 2021). Nevertheless, by aggregating and contextualizing large volumes of heterogeneous asset data, Digital Twins create a robust data foundation for AI-driven analytics and intelligent decision support, thereby delivering substantial value to the Asset Management process and enabling more efficient, predictive, and data-driven life-cycle management (Yitmen et al., 2021).

1.1.4 Blockchain

Blockchain, enabled by Distributed Ledger Technology (DLT), has emerged as a powerful technology for securely recording and verifying transactions through cryptographically linked blocks. By employing decentralized consensus mechanisms, blockchain ensures data integrity, immutability, and resilience while providing fundamental benefits such as trust, transparency, traceability, and security in information exchange (Sadeghi et al., 2022; Yaqoob et al., 2020). Within the built environment, blockchain has attracted increasing attention for supporting contract management, information management, supply chain management, and stakeholder collaboration, thereby improving accountability and coordination across construction and asset management processes (Kifokeris & Koch, 2019; Xu et al., 2022). Blockchain infrastructures are generally classified into public, private, and consortium blockchains. Public blockchains provide a fully decentralized environment but often suffer from lower transaction throughput and scalability limitations. In contrast, private blockchains offer higher performance through centralized governance, while consortium blockchains combine the advantages of decentralization and controlled access, providing a balanced solution for enterprise applications (Nanayakkara et al., 2021; Zheng et al., 2019).

A key innovation enabled by blockchain is the use of smart contracts, originally proposed by Nick Szabo, which are self-executing digital agreements that automatically enforce contractual terms without requiring third-party intermediaries (Brandin & Abrishami, 2021; Singh & Kumar, 2022). Smart contracts have demonstrated significant potential for automating and streamlining processes such as construction payments, procurement, compliance verification, and asset transactions, thereby improving efficiency, reducing administrative effort, and increasing trust among project stakeholders (Hunhevicz et al., 2022; Li & Kassem, 2021; Mannino et al., 2021; Perera et al., 2020). Nevertheless, vulnerabilities in smart contract design and implementation continue to present important security challenges that require rigorous verification and auditing (Peng et al., 2021).

Building upon smart contracts, Blockchain-powered decentralized applications (DApps) provide user interfaces and application logic that interact directly with blockchain networks, while Decentralized Autonomous Organizations (DAOs) extend this concept by enabling organizational governance through programmable rules with minimal human intervention. These technologies have the potential to improve transparency, automate

decision-making, and reduce operational costs in building operation and Asset Management. However, widespread adoption remains constrained by legal uncertainties, governance issues, and technical limitations associated with decentralized organizational models (Hunhevicz & Hall, 2020; Li & Kassem, 2021; Tezel et al., 2020).

Despite its advantages, blockchain technology continues to face challenges related to scalability, transaction throughput, and the management of Big Data, particularly in data-intensive applications such as Digital Twins and the Internet of Things (IoT). To overcome these limitations, off-chain storage mechanisms are commonly employed to store large datasets while maintaining cryptographic references on the blockchain, although this approach introduces additional security and integrity considerations. Oracles provide trusted interfaces between blockchain networks and external information sources, enabling secure integration of real-time data and ensuring data consistency across distributed systems (Banaeian Far et al., 2024; Gupta et al., 2023). Furthermore, sharding, which partitions blockchain networks into multiple parallel processing segments, significantly improves scalability by distributing transaction loads across multiple nodes while preserving decentralization, performance, and security (Perera et al., 2021; Zheng et al., 2023).

1.1.5 Blockchain-based Digital Twins

Digital Twins (DTs) enable efficient, intelligent, and transparent implementation of industrial and Asset Management (AM) services by providing continuous synchronization between physical assets and their virtual counterparts. However, the effectiveness of Digital Twins depends fundamentally on the availability of secure, trustworthy, and reliable data. Data breaches, cyberattacks, unauthorized modifications, and accidental data corruption highlight the critical importance of ensuring data integrity, authenticity, and availability throughout the Digital Twin ecosystem (Shahzad et al., 2022). In this context, Blockchain Technology (BCT) provides a robust solution by managing asset information through a decentralized distributed ledger that guarantees immutable records, secure data exchange, and trustworthy synchronization among interconnected Digital Twins (Lee et al., 2021; Rasheed et al., 2020; Suhail et al., 2022; Teisserenc and Sepasgozar, 2021a). By enabling stakeholders to securely record and trace raw process data, blockchain enhances transparency, traceability, accountability, and security across the asset life cycle (Götz et al., 2022).

A representative example of this integration is EtherTwin, a blockchain-enabled decentralized application (DApp) developed to support secure data sharing within Industry 4.0 environments. EtherTwin combines the Ethereum blockchain with Swarm decentralized storage to ensure data availability, integrity, confidentiality, and resilience while eliminating dependence on centralized data repositories. As an open-source platform, EtherTwin demonstrates significant potential for further applications in domains such as healthcare data exchange, decentralized data marketplaces, machine certification, and trusted industrial data sharing (Putz et al., 2021).

The integration of Blockchain Technology with Digital Twins further improves system reliability by enabling cross-validation of Internet of Things (IoT) sensor data, thereby ensuring trustworthy information for real-time monitoring, control, and operational decision-making. Moreover, the convergence of blockchain with Artificial Intelligence (AI)

and Machine Learning (ML) enables the development of intelligent Digital Twins capable of predictive maintenance, anomaly detection, and autonomous optimization of asset performance. To support these capabilities, blockchain-based Digital Twin frameworks have been proposed to provide secure synchronization between physical and virtual environments while ensuring trusted information exchange throughout the asset life cycle (Suhail et al., 2021, 2022).

Despite these advances, several challenges continue to limit the large-scale adoption of blockchain-enabled Digital Twins, including issues related to scalability, regulatory compliance, data privacy, interoperability, and the lack of standardized implementation frameworks. Addressing these challenges requires close collaboration among industry practitioners, technology providers, manufacturers, standards organizations, and government agencies to establish common policies, develop interoperable standards, and promote the integration of smart IoT devices, Artificial Intelligence, and Machine Learning technologies within secure Digital Twin ecosystems (Yaqoob et al., 2020)..

1.1.6 Ontologies in Building Facility Management

The application of ontologies in building facility management provides a structured, standardized, and semantically rich approach for representing, organizing, and exchanging information related to assets, building systems, and operational processes (Lei et al., 2021). By establishing common vocabularies and relationships among data entities, ontology-based models improve semantic interoperability and facilitate information sharing across heterogeneous digital platforms. In addition, different maintenance strategies, including preventive, condition-based, and predictive maintenance, provide decision-making frameworks that support more effective planning and management of facility operations (Bouabdallaoui et al., 2021). The adoption of Asset Information Models (AIMs) further enhances building facility management by integrating structured and unstructured information with real-time operational data, thereby enabling data-driven asset management and predictive maintenance strategies (Hellenborn et al., 2024). Consequently, the integration of an ontology-based AIM with predictive maintenance capabilities enables facility managers to make informed decisions, optimize asset performance, improve operational efficiency, and extend the service life of building facilities (Heaton & Parlikad, 2020).

Within the Architecture, Engineering, Construction, and Facility Management (AEC-FM) industry, ontology-based approaches have been widely adopted to support Building Information Modeling (BIM) and improve interoperability between digital systems. Representative examples include the Building Topology Ontology (BOT) and its alignment with established semantic frameworks such as BrickSchema, IFCOWL, Project Haystack, Real Estate Core (REC), and SAREF, all of which facilitate standardized representation and integration of building information across multiple applications (Brick Ontology, 2021). Despite these advances, a significant gap remains in the development of ontologies specifically tailored to predictive maintenance in building facilities (Bouabdallaoui et al., 2021). This limitation hinders the standardization, semantic interoperability, and seamless exchange of information among heterogeneous systems, thereby constraining the effective implementation of predictive maintenance and intelligent Asset Management practices across the building life cycle (Mahdavi & Taheri, 2017).

1.1.7 Predictive Maintenance

Predictive maintenance is a proactive maintenance strategy that leverages data analytics, Machine Learning (ML) algorithms, and real-time monitoring to predict when equipment or machinery is likely to fail, enabling maintenance teams to schedule timely interventions before failures occur (Yitmen et al., 2023). The primary objective of predictive maintenance is to minimize equipment downtime, extend asset service life, optimize maintenance scheduling, and reduce maintenance costs, while improving the overall reliability and performance of physical assets (Hosamo et al., 2022).

This approach relies on the continuous collection and analysis of data from multiple sources, including Internet of Things (IoT) sensors, historical maintenance records, operational logs, and equipment performance indicators. These heterogeneous datasets are processed to develop predictive models capable of supporting real-time asset monitoring, identifying patterns and anomalies, estimating equipment degradation, and generating early warnings of potential failures (Tiddens et al., 2022). By detecting emerging faults before they develop into critical failures, predictive maintenance enables maintenance activities to be planned during scheduled maintenance windows, thereby avoiding costly unplanned disruptions and improving operational continuity (Hellenborn et al., 2024).

The adoption of predictive maintenance provides substantial operational and economic benefits, including reduced equipment downtime, improved asset reliability and availability, optimized resource utilization, lower maintenance expenditures, and a reduced risk of equipment damage. Furthermore, predictive maintenance enhances workplace safety and environmental protection by minimizing the likelihood of unexpected equipment failures that could endanger personnel, disrupt operations, or cause environmental incidents (Bouabdallaoui et al., 2021; Villa et al., 2021). As a result, predictive maintenance has become a key enabler of intelligent Asset Management, supporting data-driven decision-making and maximizing asset value throughout the entire asset life cycle.

1.1.8 Asset Information Model

An Asset Information Model (AIM) is a comprehensive and structured repository of information relating to the physical assets, systems, and operational processes required to support the effective management, operation, and maintenance of built assets. It serves as a centralized source of asset information by integrating detailed data on building components, systems, operational activities, and life-cycle processes, thereby facilitating informed decision-making throughout the asset life cycle (Heaton & Parlikad, 2020). The British Standards Institution (BSI, 2014) defines an AIM as "data and information that relates to assets to a level required to support an organization's asset management system," while ISO 19650-1:2018 defines the AIM as the information model associated with the operational phase of an asset and provides guidance for the creation, management, maintenance, and use of asset information throughout the building life cycle (ISO, 2018).

Within the ISO 19650 framework, Organizational Information Requirements (OIR) establish the strategic information needed to achieve organizational objectives, which subsequently define the Asset Information Requirements (AIR). The AIR determines the scope, structure, and content of the Asset Information Model, ensuring that the information captured supports organizational asset management objectives and operational decision-

making (ISO, 2018). Consequently, effective alignment between OIR, AIR, and the AIM is essential for delivering reliable information across all stages of the asset life cycle.

Beyond its role as an information repository, an Asset Information Model provides the digital foundation for implementing Digital Twin (DT) technologies by integrating real-time operational data with historical and design information. This integration enables continuous monitoring of asset performance, supports predictive maintenance, and improves data-driven decision-making, thereby reducing the risk of unexpected failures, increasing asset reliability, and enhancing the overall efficiency of building operations (Bouabdallaoui et al., 2021). However, although contemporary Asset Management systems can collect and store large volumes of asset information, they often have limited capabilities for advanced data analytics, semantic interoperability, and seamless integration across the entire asset life cycle (Farghaly & Hagras, 2022; Hellenborn et al., 2024).

An Asset Information Model incorporates both structured data, including databases, schedules, sensor information, and 3D Building Information Modeling (BIM) models, and unstructured data, such as documents, images, audio recordings, videos, and technical reports, thereby providing a comprehensive knowledge base for asset management (Hellenborn et al., 2024). Although existing standards support the use of BIM information during the operation and maintenance (O&M) phase, there remains a lack of comprehensive frameworks that effectively integrate strategic, procedural, and technological standards within a unified digital ecosystem (Heaton & Parlikad, 2020). To overcome these limitations, the semantic structuring of AIM data through an ontology-based approach can significantly improve interoperability and facilitate seamless integration between the Asset Information Model and a Digital Twin platform. Nevertheless, manually developing and maintaining ontology-based information structures is labor-intensive and difficult to scale. Therefore, the adoption of ontology-based knowledge graphs has been proposed to automate the transformation of heterogeneous asset information into semantically enriched Asset Information Models, enabling more intelligent, interoperable, and scalable asset management solutions (Yitmen et al., 2023)..

1.2 Purpose and Objectives

The project aims to create a digital platform prototype that integrates emerging technologies such as Digital Twins, Blockchains, and Artificial Intelligence with Asset Management Processes in the smart built environment to ensure secure and accessible data processing. In alignment with the study's purpose, mainly four research questions are posed:

Q1: How can a digital platform prototype be developed to fully realize the potential of smart Asset Lifecycle Management (ALM) within the digital ecosystem?

Q2: What are the essential features, requirements, and system architecture needed for the digital platform prototype to successfully integrate Blockchain and Digital Twin (DT) technologies into the digital ecosystem?

Q3: How can the digital platform prototype be applied to autonomously and collaboratively simulate and optimize predictive cases for smart ALM?

Q4: What potential benefits can the digital platform create for facility operators, real estate professionals, and end users (such as inhabitants)?

1.3 Expected Results and Effects

The project aims to develop a Blockchain-based Digital Twin (DT) platform for smart asset lifecycle management, with a particular emphasis on innovative operation and maintenance (O&M) applications. The platform integrates Blockchain, Digital Twin, Artificial Intelligence (AI), and Machine Learning (ML) technologies to deliver transparent, traceable, secure, and real-time access to asset information while providing dynamic process visualization and advanced decision-support capabilities. By enabling continuous monitoring and trusted information exchange, the platform improves operational efficiency, significantly reduces the time and cost associated with managing O&M activities, and supports secure and transparent data sharing across blockchain-enabled ecosystems throughout the asset life cycle.

A key component of the platform is an AI- and Machine Learning-driven predictive maintenance module, which continuously analyzes operational and sensor data to predict potential equipment failures before they occur. This capability minimizes unplanned downtime, improves asset reliability and availability, reduces maintenance costs, and decreases energy waste caused by equipment malfunction, degradation, or improper operation. Furthermore, the integration of Blockchain technology enables the implementation of smart contracts, which automatically execute predefined actions—such as releasing payments, transmitting information, initiating procurement processes, or triggering maintenance workflows—when specified contractual or operational conditions are satisfied during the asset life cycle.

The project also seeks to improve information flow and accelerate the digital transformation of the Architecture, Engineering, Construction, Operation, and Facility Management (AECO-FM) sector, thereby contributing to the Smart Built Environment Impact Logic 2.0. In particular, the platform is designed to support the achievement of ambitious long-term objectives, including reducing project time and costs by 33% while decreasing climate impact by 40% through more efficient, intelligent, and sustainable asset management practices.

Beyond its technological contributions, the project is expected to generate significant value for industrial partners as well as organizations operating within the facility management and real estate sectors. It will promote knowledge dissemination at both national and international levels through collaboration with academic institutions, industry partners, and public stakeholders. By providing a collaborative digital platform that directly connects facility operators, property owners, real estate professionals, service providers, and building occupants, the project fosters value creation across the stakeholder ecosystem while strengthening governance through enhanced connectivity, communication, collaboration, transparency, and data-driven decision-making.

1.4 Organization

The project requires a multidisciplinary approach, integrating expertise in building technology, Asset Lifecycle Management (ALM), the Internet of Things (IoT), Digital Twin (DT) technology, Blockchain, Artificial Intelligence (AI), and data-driven asset management. To address this interdisciplinary scope, the project team brings together complementary competencies from both academic and industrial partners. The participating researchers contribute extensive expertise across the project's core research domains and provide the scientific knowledge required to successfully implement the activities defined in the work packages. In addition, a project-funded research assistant will be recruited to support research activities within the three core disciplines of the project, while also benefiting from close collaboration with researchers and industry professionals in an interdisciplinary research environment.

The principal academic partners include the Department of Construction Engineering and Lighting Science at the School of Engineering, Jönköping University; the Department for Industrial Building and Interdisciplinary Planning at the Faculty of Civil Engineering, Vienna University of Technology; the Department of Computer Science at the University of Turin; and the Department of Civil Engineering at the Faculty of Engineering, University of Manchester. These institutions share a common vision of advancing knowledge at the intersection of digitalization, information technology, and smart asset management, with a particular focus on facility management (FM) and real estate sectors. Their complementary expertise provides a strong scientific foundation for developing innovative solutions that integrate Digital Twin, Blockchain, IoT, and AI technologies.

The opportunity to undertake this collaborative and multidisciplinary research on a Blockchain-enabled Digital Twin platform for smart Asset Lifecycle Management enables the participating universities to contribute to the rapidly evolving Industry 4.0 ecosystem and the international advancement of blockchain-enabled Digital Twin technologies. The project further strengthens long-term collaboration among the participating institutions by connecting research activities with educational programs, promoting joint supervision, knowledge exchange, and the integration of Digital Twin and Blockchain technologies into teaching and research, thereby enhancing scientific capacity within the built environment domain.

The industrial partners, representing the facility management, real estate, and built environment sectors, share a strong commitment to accelerating the adoption of Digital Twin and Blockchain technologies for intelligent asset lifecycle management. The research project is jointly owned by both academic and industrial partners, reflecting a shared responsibility for knowledge creation, technology development, and practical implementation.

Pythagoras AB contributes extensive expertise in developing digital platforms and information management solutions for Property, Real Estate, and Facilities Management. The company also provides strategic business consulting in the areas of Smart Buildings, Property Management, and Facilities Management, and has developed an advanced

platform supporting Smart Buildings and IoT integration to enable the digital transformation of property operations.

Plan B AB contributes expertise in sustainable urban development and digital construction by delivering innovative Building Information Modeling (BIM)-based solutions for climate-smart, sustainable, and socially inclusive built environments. The company combines advanced technical competence with a strong commitment to sustainable development and social responsibility, supporting the integration of digital technologies into community and infrastructure development.

Throughout the project, the collaboration between academic institutions and industrial partners will foster the development of strong research and innovation networks, enabling the co-creation of system architecture, ontology-based knowledge models, and advanced Digital Twin applications. The project will also include the design, implementation, testing, validation, and evaluation of the Blockchain-enabled Digital Twin platform prototype across multiple industrial use cases, demonstrating its applicability for intelligent operation, maintenance, and Asset Lifecycle Management within the built environment.

2 METHOD AND IMPLEMENTATION

2.1 Project Phases

The project spans three years and is structured into five Work Packages (WPs), following the approach illustrated in Figure 1:

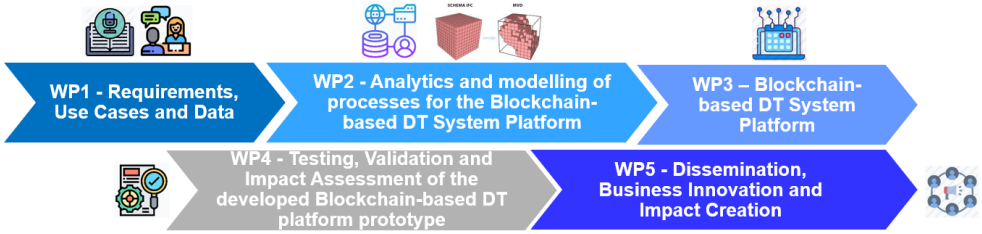

Figure. 1 Work Packages for development of the Blockchain based DT platform.

WP1: Requirements, Use Cases and Data During this phase, all functional and non-functional requirements, together with the corresponding Key Performance Indicators (KPIs) for Asset Lifecycle Management (ALM), are identified and defined. Use cases are developed to capture, describe, validate, and categorize these requirements, while reference scenarios are established to support system design and evaluation. Based on these requirements, the technical specifications are formulated, and the overall Blockchain-based system architecture is designed to provide a secure, scalable, and interoperable foundation for the platform.

WP2: Analytics and modelling of processes for the Blockchain-based DT System This Work Package focuses on developing the methodologies, digital infrastructure, and analytical models required to support data-driven analytics for Blockchain-based Digital Twin systems in smart Asset Lifecycle Management (ALM). It defines the functional requirements and technical design specifications for the analytics framework and establishes an analytical platform that supports blockchain-enabled Asset Management Processes (AMP). As part of this work, a comprehensive Asset Information Model (AIM) is developed to represent asset information, uncertainty, and causal relationships, together with an anomaly detection system for continuous monitoring and predictive analysis. To ensure standardized process modeling and interoperability, Business Process Modeling Notation (BPMN), following the standards of the buildingSMART community, is adopted, with the Model View Definition (MVD) Method serving as the primary approach for modeling and information exchange.

WP3: Blockchain-based DT System Platform This phase focuses on the design, development, and management of a Blockchain-based Digital Twin (DT) platform for smart Asset Lifecycle Management (ALM). The activities include designing the blockchain-enabled DT architecture, implementing data-driven analytics as a cognitive service for ALM, and

generating actionable asset knowledge to support proactive and intelligent asset management. The phase also identifies the required Internet of Things (IoT) sensors, smart devices, and Building Automation System (BAS) platforms needed to establish seamless connectivity between physical assets and their digital counterparts.

To enable integrated and intelligent asset management, interoperability is established between these systems and Building Operations and Maintenance Systems (BOMS), while the integration of IoT, Digital Twins, and Asset Information Management (AIM) platforms provides a unified environment for real-time data acquisition, information management, and operational decision support. Furthermore, an AI- and Machine Learning (ML)-powered predictive maintenance module is developed to simulate, predict, and optimize maintenance scenarios through both autonomous and collaborative decision-making, thereby improving asset reliability, operational efficiency, and maintenance planning.

To ensure transparency, traceability, security, and trust throughout the Asset Management Process (AMP), all platform components are interconnected within the Blockchain-based Digital Twin ecosystem and integrated through blockchain-enabled decentralized smart contracts. This secure and interoperable architecture enables trusted information exchange, automated workflow execution, and reliable asset life-cycle management across all participating stakeholders.

WP4: Testing, Validation, and Impact Assessment of the developed Blockchain-based DT platform prototype This phase focuses on the testing, validation, and evaluation of the interoperability between the Digital Twin (DT), Blockchain, and smart Asset Lifecycle Management (ALM) systems within dynamic, real-world environments. Validation is conducted in pilot buildings, including commercial, educational, and residential facilities, through multiple use cases involving industry practitioners such as facility management (FM) specialists, asset managers, and prospective end users.

A comprehensive validation program is implemented to assess the usability, functionality, interoperability, and effectiveness of the integrated solution under operational building conditions. Following each validation cycle, operational and user-generated data are systematically collected and analyzed to evaluate the performance, impact, and practical benefits of the Blockchain-based Digital Twin platform for smart ALM. In addition, qualitative feedback is obtained through interviews, workshops, and stakeholder engagement activities to identify implementation challenges, capture lessons learned, and gather recommendations for further improvements. The findings are used to iteratively refine the platform, ensuring that the solution meets both technical requirements and user needs while supporting reliable and scalable deployment in real-world asset management environments.

WP5: Dissemination, Business Innovation, and Impact Creation This Work Package coordinates the dissemination, communication, exploitation, and standardization activities of the project while supporting the development of sustainable business models for the Blockchain-based Digital Twin (DT) platform for smart Asset Lifecycle Management (ALM). A dedicated project website is designed, developed, and launched to communicate project objectives, activities, progress, and outcomes to stakeholders, industry, academia, and the wider public.

The project's scientific and technical outcomes are compiled into comprehensive reports that emphasize the practicality, usability, and scalability of the proposed methodology and platform. The research findings are disseminated through peer-reviewed journal publications, international conference presentations, workshops, and stakeholder engagement activities to maximize scientific impact and knowledge transfer.

To enhance the exploitation and long-term adoption of the project results, this work package targets key stakeholder groups by disseminating relevant findings, producing communication and promotional materials—including the project website, brochures, and digital media—and identifying opportunities for technology transfer and commercialization. In addition, it supports the development of innovative and sustainable business models for the Blockchain-based Digital Twin platform, fostering the wider implementation of smart Asset Lifecycle Management (ALM) solutions across facility management, real estate, and built environment sectors.

2.2 Project Deliverables

The proposed Digital Twin (DT) platform, designed to support decentralized data sharing, addresses several critical challenges facing the real estate and facility management (FM) sectors by providing innovative solutions for smart Asset Lifecycle Management (ALM). The platform delivers the following key capabilities:

- Asset Information Model (AIM) platforms integrated with Internet of Things (IoT) networks and Digital Twin (DT) environments: The project establishes seamless interoperability between AIM, IoT infrastructures, Digital Twins, and Building Operations and Maintenance Systems (BOMS). Data generated from IoT networks, sensors, and interconnected smart devices are continuously collected, integrated, analyzed, and managed within the platform. The Digital Twin functions as a secure, real-time, and information-rich interface that supports continuous monitoring, visualization, and control throughout the asset life cycle.
- Interrogative and predictive modeling: The Machine Learning (ML)-enabled Digital Twin platform analyzes both historical and real-time operational data to assess current asset performance and predict future behavior. An AI- and ML-powered predictive maintenance module is developed to autonomously and collaboratively simulate maintenance scenarios, detect anomalies, optimize maintenance strategies, and support proactive decision-making for Asset Lifecycle Management.
- Blockchain-enabled environment for trust, traceability, and transparency: A proof-of-concept platform is developed to demonstrate the feasibility and performance of blockchain-enabled smart building management applications through representative simulation scenarios. By synchronizing the Digital Twin platform with a Blockchain Records Management Service, the system securely records and tracks changes to asset information, ensuring trust, traceability, transparency, data integrity, and secure information exchange throughout the asset life cycle.
- Smart contract applications: The platform utilizes blockchain-enabled smart contracts to automatically execute predefined actions—such as releasing payments, transmitting information, initiating procurement processes, or triggering maintenance workflows—when specified operational or contractual conditions are satisfied during Asset Lifecycle Management. The automation of these processes

reduces human error, lowers administrative and service costs, minimizes operational downtime, improves workflow efficiency, and supports more reliable, transparent, and intelligent asset management across the built environment.

3 PROJECT RESULTS

3.1 Requirements, Use Cases and Data

3.1.1 Requirements

Smart Asset Lifecycle Management (ALM) in building facilities aims to optimize the management of assets throughout their entire life cycle, encompassing planning, design, acquisition, operation, maintenance, renewal, and decommissioning. Achieving effective Asset Management (AM) requires the integration of advanced digital technologies, including Building Information Modeling (BIM), Digital Twins (DTs), the Internet of Things (IoT), Artificial Intelligence (AI), Machine Learning (ML), and predictive maintenance solutions. These technologies enable data-driven decision-making and support the monitoring of Key Performance Indicators (KPIs) that evaluate the extent to which asset management strategies achieve organizational objectives, operational excellence, sustainability, and long-term asset value.

The core requirements and corresponding KPIs for smart ALM in building facilities are summarized below.

i. Asset Information Management

Requirement:
Establish a comprehensive Asset Information Management (AIM) environment that organizes, manages, and provides secure access to accurate, complete, standardized, and up-to-date asset information, including technical specifications, maintenance history, operational status, performance indicators, inspection records, and life-cycle documentation.

KPIs:

- Data Accuracy: Percentage of asset information that is complete, consistent, and error-free.
- Data Accessibility: Average time required to retrieve relevant asset information.
- Compliance Rate: Degree of compliance with information management standards such as ISO 19650.
- Data Update Frequency: Frequency with which asset information is synchronized and updated.

ii. Operational Efficiency

Requirement:
Optimize the utilization, performance, and availability of physical assets to improve operational efficiency, reduce operational costs, and maximize asset value throughout the life cycle.

KPIs:

- Asset Utilization Rate: Percentage of productive asset usage relative to total available operating time.

- Energy Consumption: Energy consumed by each asset over time, monitored through IoT-enabled systems.
- Operational Downtime: Total duration during which assets are unavailable for operation.
- Facility Performance: Comparison between planned and actual operational performance.

iii. Predictive Maintenance and Condition Monitoring

Requirement:
Implement predictive maintenance and continuous **condition monitoring** using AI, Machine Learning, IoT sensors, and Digital Twin technologies to anticipate failures, optimize maintenance schedules, and improve asset reliability.

KPIs:

- Maintenance Prediction Accuracy: Accuracy of AI and ML models in predicting maintenance requirements and equipment failures.
- Mean Time Between Failures (MTBF): Average operating time between consecutive failures.
- Maintenance Cost Reduction: Percentage reduction in maintenance costs achieved through predictive maintenance.
- Maintenance Response Time: Time required to respond to detected maintenance issues.
- Failure Rate: Frequency of unexpected equipment failures.

iv. Sustainability and Environmental Impact

Requirement:
Ensure that Asset Lifecycle Management contributes to sustainability objectives by minimizing environmental impacts, reducing energy consumption, improving resource efficiency, and supporting circular economy principles.

KPIs:

- Carbon Footprint: CO_2 emissions associated with asset operation and maintenance.
- Energy Efficiency: Energy consumption per square meter or unit of operational output.
- Waste Reduction: Reduction in material waste and energy losses during operation and maintenance.
- Water Use Efficiency: Water consumption per asset, facility, or operational function.

v. Digital Twin (DT) Integration

Requirement:
Integrate Digital Twin (DT) technology with Building Information Modeling (BIM), IoT, and Asset Information Management (AIM) to enable real-time monitoring, simulation, predictive analytics, and performance optimization throughout the asset life cycle.

KPIs:

- Real-time Monitoring Accuracy: Degree to which the Digital Twin accurately reflects the current condition of physical assets.
- Model Update Frequency: Frequency of synchronizing the Digital Twin with live operational data.
- Simulation Accuracy: Accuracy of Digital Twin simulations in predicting future asset performance and maintenance requirements.
- Downtime Reduction: Reduction in operational downtime achieved through Digital Twin-enabled predictive insights.

vi. Collaboration and Information Sharing

Requirement:
Promote effective collaboration and secure information sharing among facility managers, asset managers, operators, maintenance personnel, service providers, and other stakeholders through integrated digital platforms.

KPIs:

- Information Sharing Efficiency: Time required to exchange critical asset information among stakeholders.
- Collaboration Tool Usage: Percentage of Asset Management activities supported through collaborative digital platforms.
- Feedback Implementation Time: Time required to evaluate and implement stakeholder feedback within operational workflows.

By establishing these requirements and continuously monitoring the associated Key Performance Indicators (KPIs), organizations can evaluate and improve the effectiveness of smart Asset Lifecycle Management in building facilities. The integration of Building Information Modeling (BIM), Digital Twins (DTs), IoT, Artificial Intelligence (AI), Machine Learning (ML), and predictive maintenance technologies enable real-time monitoring, intelligent decision support, continuous performance optimization, and sustainable asset management throughout the entire asset life cycle.

3.1.2 Use Cases

Use Case 1

This research investigates the comfort-level indicators of an 18 m^2 conference room located in Stockholm and owned by Pythagoras AB, as illustrated in Figure 2. Environmental data were continuously collected using Internet of Things (IoT) sensors, including variables such as day, hour, occupancy, temperature, CO_2 concentration, and relative humidity, to monitor and evaluate the indoor environmental conditions of the space. The objective of this case study is to design and implement a blockchain-enabled smart contract between facility managers (FM) and building owners using the Remix Ethereum platform. The smart contract facilitates secure data registration, visualization of the environmental status, and data-driven decision-making through predictive analysis within a Digital Twin (DT) environment.

The developed smart contract incorporates several core functionalities to support intelligent Operation and Maintenance (O&M). The "Add Room Data" function enables authorized users to record environmental parameters, including day, hour, occupancy, CO_2 concentration (300–1000 ppm), temperature (20–25°C), and relative humidity (40–60%).

The "Get Environment Status" function evaluates the recorded sensor data against predefined comfort thresholds for CO_2, temperature, and humidity based on user-specified day and hour values, thereby verifying whether indoor environmental conditions remain within acceptable operating limits. The "Get Room Data" function retrieves historical sensor records corresponding to the selected day and hour, enabling retrospective analysis of environmental performance. Furthermore, the "Predict Environment" function applies predictive analysis to generate alerts and recommendations for asset adjustments, thereby supporting predictive maintenance and proactive facility management, as presented in Table 2 and Figure 8.

The principal dynamic variables—occupancy, temperature, CO_2 concentration, and humidity—were continuously monitored over a 24-hour period, representing critical operational parameters during the Operation and Maintenance (O&M) phase of the Digital Twin. These real-time and historical datasets provide the basis for predictive maintenance (PM) by supporting data visualization, information management, performance analysis, anomaly detection, and predictive analytics. The smart contract is specifically designed to leverage these data for Predictive Asset Management (PAM) by enabling secure data storage, real-time visualization, retrieval of current and historical asset information for decision support, and automated alerts that facilitate proactive maintenance interventions.

The customized smart contract was implemented in Solidity and deployed on the Sepolia testnet, a public Ethereum test network, to validate blockchain transactions and verify the operational functionality of the proposed framework. The contract was developed, tested, and deployed using Remix Ethereum, a browser-based Integrated Development Environment (IDE) that supports Solidity programming and execution on the Ethereum Virtual Machine (EVM). The Sepolia testnet provides a secure and cost-free environment for validating decentralized applications (DApps) and smart contracts before deployment on the Ethereum main network, thereby enabling reliable testing of blockchain-enabled Digital Twin applications without financial risk (Celik et al., 2023; Wöhrer & Zdun, 2021).

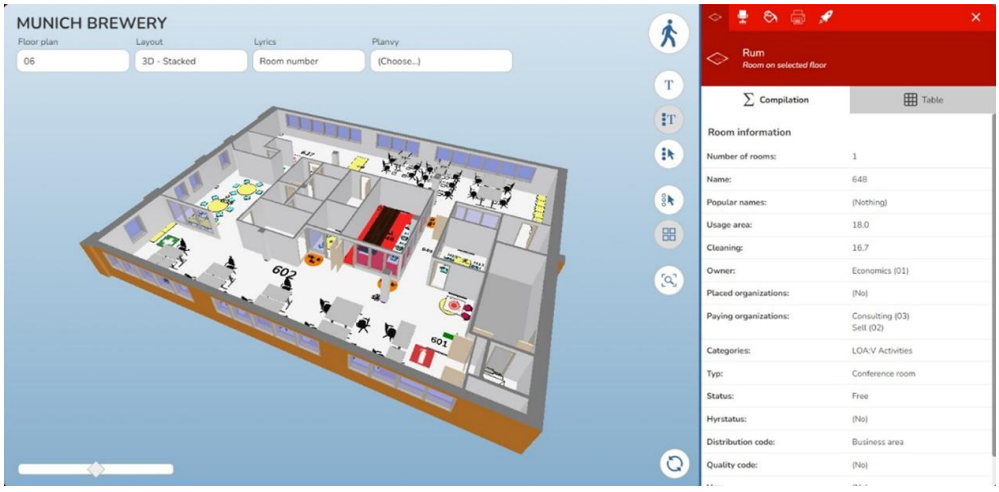

Figure 2. Case study 1 involving conference room information (Tavakoli et al., 2023)

Use Case 2

To demonstrate the application of advanced building management technologies, a comprehensive case study was conducted in a four-story administrative building (K-Building) located at Jönköping University, Sweden. The study utilized a comprehensive dataset spanning the period 2020–2023, incorporating multiple parameters essential for building operations, energy management, and facility management. The monitored data included indoor temperature, district heating consumption, district cooling consumption, electricity usage, and total energy consumption, all collected, processed, and analyzed at hourly intervals to support continuous performance assessment.

The collected data were analyzed and presented through a user-friendly interactive dashboard developed using the Dash library in Python. Serving as the primary user interface, the dashboard provides an intuitive environment for exploring, visualizing, and interpreting building performance data. It supports visualization at multiple temporal resolutions, including hourly, daily, and monthly intervals, while allowing users to define customized analysis periods for detailed investigation of operational trends, seasonal variations, and energy consumption patterns. The dashboard was designed with a strong emphasis on usability, accessibility, and functionality, enabling stakeholders—including facility managers, energy auditors, building operators, and tenants—to interact with relevant information according to their roles and responsibilities.

The dashboard delivers a comprehensive overview of building performance by continuously monitoring key performance indicators (KPIs) related to energy consumption, building operation, and indoor environmental conditions. Through intuitive visualizations, including radar charts, line graphs, and interactive performance indicators, the platform identifies operational deviations, performance anomalies, and potential inefficiencies, transforming complex datasets into actionable information. These visual analytics support data-driven decision-making, enabling stakeholders to identify opportunities for optimizing energy consumption, improving indoor environmental quality, enhancing occupant comfort, and reducing operational costs. In addition, the platform allows users to customize threshold values for environmental parameters, ensuring compliance with local regulations, organizational policies, and operational objectives.

A further contribution of the study is the implementation of role-based access and data transparency, ensuring that each stakeholder has access only to information relevant to their responsibilities. This structured access model promotes secure information sharing, improves collaboration among stakeholders, and streamlines the decision-making process for building operation and maintenance by providing timely, accurate, and role-specific insights.

Overall, this case study demonstrates the significant potential of integrating advanced data analytics, interactive visualization, and digital building management technologies into modern facility management practices. By combining historical and real-time operational data, the proposed approach supports proactive monitoring, performance optimization, and intelligent decision-making, thereby improving operational efficiency, energy performance, sustainability, and occupant satisfaction. The study further illustrates how

data-driven strategies can proactively address challenges in building operations and contribute to the development of a more sustainable, resilient, and intelligent built environment.

Figure 3 illustrates the underlying framework upon which the platform prototype is developed.

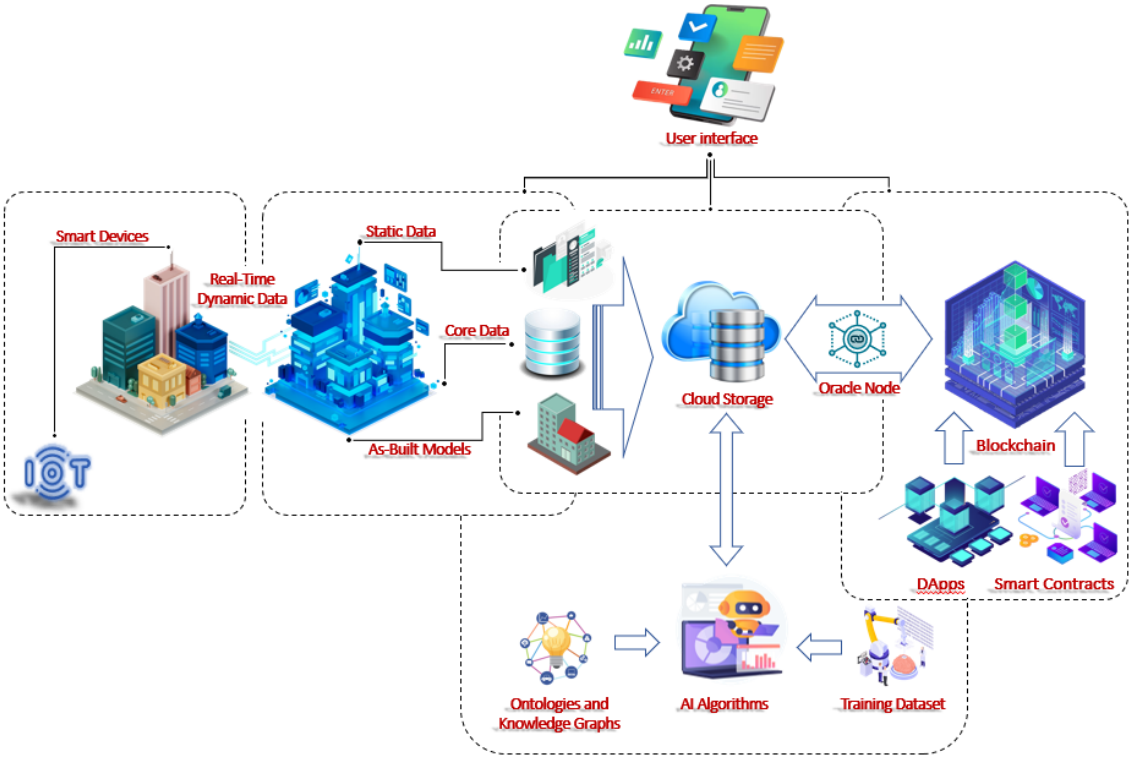

Figure 3. The platform prototype's conceptual framework.

3.1.3 Data

3.1.3.1 Data Collection

3.1.3.1.1 Qualitative Data

A. Asset Information Requirements for Blockchain-Based Digital Twins: A Data-Driven Predictive Analytics Perspective

Interviews

Semi-structured interviews were conducted using a structured interview guide comprising pre-defined questions organized around several thematic areas while allowing flexibility for in-depth discussion and follow-up questions. The interview data were audio-recorded, transcribed, and analyzed using NVivo qualitative data analysis software through a systematic thematic analysis approach. The demographic characteristics of the interview participants are presented in Table 1.

Table 1. Interviewees: Overview

Position (Role)	Type of Organization	Company Size*	Operating Region	Years of Experience	Duration**
CPO	Real Estate & FM Services	Large	Stockholm	25	55
Owner/Founder	Software Development	Small	Malmö	10	55
Key Account Manager	Provider of Management Software	Medium	Stockholm	25	55
Sr. Business Developer	Real Estate Company	Large	Stockholm	56	55
Head of FM Services	PropTech Company	Medium	Gothenburg	7	60
Digital Innovation Strategist	Real Estate Company	Large	Gothenburg	5	65
BIM Coordinator	Architectural Firm	Medium	Ireland	17	50
Information & BIM Strategist	Facility Management Company	Large	Stockholm	20	55
Owner/Founder	Management Consulting	Small	Stockholm	25	65
Energy Engineer	Facility Management Company	Large	Stockholm	13	60
CEO	Provider of Management Software	Medium	Stockholm	30	65
Head of research	R&D and Consultancy	Small	England	8	50

*Small: 0-50 employees, Medium: 50-250 employees, Large: 250+ employees. **Interview duration in minutes

Thematic Analysis

The thematic analysis identified seven major themes representing the key requirements, opportunities, and challenges associated with implementing Blockchain-based Digital Twins for predictive analytics and Asset Management. These themes include: (i) prerequisites and challenges for predictive analytics, (ii) development and maintenance of Asset Information Models (AIMs), (iii) maintaining accurate as-is/as-built information within AIMs, (iv) characteristics and challenges of the Architecture, Engineering, Construction, Operation, and Facility Management (AECO-FM) industry, (v) technical aspects of Blockchain Technology (BCT), (vi) practical applications and use cases of

blockchain, and (vii) the integration and synergies between Blockchain Technology and Artificial Intelligence (AI). Table 2 summarizes these themes by highlighting the principal concepts, challenges, and opportunities identified during the interviews.

Table 2. Coded Themes from Interviews

Theme	Description
1. Prerequisites & challenges for predictive analytics	- First, ML requires a meta data model i.e., a data structure for core asset data that is suitable for AI, e.g., ontologies like Bricks, Haystack or Real Estate Core. Second, detailed data/information about the assets facilitating the O&M process. Third, data measuring the performance of the asset in question, real-time and historical. - Formulating the problem mathematically for advanced multivariable predictive analytics is challenging. - ML requires a lot of structured data to train and validate the models.
2. Creation of an AIM	- BIM models are generally not delivered in as-built condition. Cost focus leads to suboptimizations such as modeling assets in one space and referring to them in others. Assets in the BIM model are suggestions, the actual asset that is installed is not specified. Sometimes this information is delivered separately without any connection to the model or in formats that are challenging to integrate into the AIM. - Creating a structured AIM is resource intensive and the benefits are not instantly accessible. Due to the general lack of structured data the AECO-FM industry has an especially poor starting point. - Ideally the 3D drawing space needs to be auto translated into building knowledge graphs as they are easily become too large to be effectively maintained by humans.
3. Ensuring as-is/as-built status of AIM	- Interoperability is vital to enable editing, ensuring the as-is/as-built state of the AIM. - The process of updating the AIM needs to be integrated into the daily work processes.
4. AECO-FM Industry Characteristics	- Divergence in digital maturity between actors. - Generally low digital maturity in the industry. - Data and information segregation.
5. Technical aspects of BCT	- The transaction speed of blockchain makes it inappropriate for high data rates, off-chain storage with references on chain could circumvent this issue. - Some BCT protocols are energy intensive. - It should not cost too much in terms of computing power and performance to decrypt anything that is not of particularly high dignity. - Blockchains are difficult to program, cost of implementation could be higher than the potential value.
6. Use cases of BCT	- Access control credentials, which credentials has access to what spaces during what time. - Who has access to what information in the DT. - Keeping track of service intervals, protocols, inspection logs, pictures, state of assets, active/retired assets. - Transactions in general requires an immutable state, e.g., data/information handovers could utilize BTC to establish consensus regarding what was delivered by whom and when. - If there is a need for security of a certain type of information blockchain could be useful. - The level of encryption should stand in proportion to the level of sensitivity/importance of the information/data. Sensitivity/importance of data can vary between different types of facilities.
7. BCT and AI synergies	- Recording data and decisions made by AI provides transparency and traceability promoting higher trust and ultimately better results.

B. Blockchain-based digital twin data provenance for predictive asset management in building facilities

Interviews

To obtain expert perspectives on blockchain-based Digital Twin data provenance, semi-structured interviews were conducted via video conferencing with participants' informed consent for recording and transcription. The interview protocol was developed by the research team based on recent literature and designed to investigate the study's research questions while allowing participants to freely discuss emerging issues. The demographic profile of the interviewees is presented in Table 3.

Participants were recruited through the professional networking platform LinkedIn, targeting international experts in Blockchain Technology, Digital Twins (DTs), and building facility management. Invitations were sent to 19 professionals, of whom eight experts agreed to participate in the study. Following transcription, the interview data were systematically analyzed using NVivo through thematic coding.

Table 3. Interviewees' demographics

Position (Role)	Type of Organization	Company Size*	Operation Region	Years of Experience	Duration**
Digital Twin Specialist	Metaverse consultancy	Small (30)	Gothenburg	20	65
CEO	IT Services and IT Consulting	Small (16)	Slovakia	25	61
CEO	IT Services and IT Consulting	Small (10)	England	20	57
Digitalization Sustainability Manager	construction and infrastructure business	Medium (125)	Norway	5	59
Chief Architect	IT Services and IT Consulting	Large (10000)	San Francisco	30	62
CSO	IT Services and IT Consulting	Small (20)	Germany	12	55
Senior Lecturer	Higher Education	Medium (150)	Ireland	38	58
Post-Doctoral Fellow	Higher Education	Large (10000)	Canada	12	60

*Small:0-50 employees, Medium: 50-250 employees, Large: 250+ employees. **Interview duration in minutes

Thematic Analysis

The interview findings were coded according to the research questions, and the resulting themes are summarized in Table 4. The analysis indicates that integrating Blockchain Technology into Asset Management offers several important benefits, including improved data trustworthiness, transparency, security, traceability, operational efficiency, and enhanced predictive analytics. The participants identified several critical success factors for implementing blockchain-enabled platforms, including standardization, data provenance, data synchronization, digital asset representation, and metadata management. Nevertheless, significant implementation challenges remain, including the management of large data volumes, integration of heterogeneous information sources, interoperability

issues, and the need for stronger collaboration among software vendors, technology providers, and industry stakeholders. Overall, the findings demonstrate that blockchain has considerable potential to transform Asset Management by enabling secure, transparent, and trustworthy information management throughout the asset life cycle.

Table 4. Themes and descriptions of interviews

Themes	Descriptions
1. Significance of blockchain technology in Asset Management	- As a facility manager: trustworthy information needed to be hunted regarding any conflict action. - Improved transparency: BCT can provide greater transparency into asset ownership, transactions, and other key data. This can help prevent fraud, reduce errors, and improve data quality. - Increased security: BCT is highly secure, using cryptographic algorithms and distributed ledgers to ensure that data is protected from tampering or hacking. - Greater efficiency: By enabling automated and decentralized transactions, BCT can improve the speed and efficiency of asset management processes. - Improved tracking and traceability: With blockchain, asset managers can track assets more effectively throughout their lifecycle, from acquisition to disposition. This can help improve the accuracy of asset valuations and reduce the risk of errors or fraud. - Enhanced predictive analytics: With blockchain, asset managers can collect and analyse data from a range of sources to develop predictive models that can help anticipate maintenance needs, identify potential issues before they arise, and optimize asset utilization.
2. The necessity of Data Provenance	- The need of standardization for dynamic data that created and transfer on blockchain platform. - Merging and collaborating the required dynamic data from asset information model and providing the accessibility for smart contract implementation. - Quality assurance of data, Traceability of assets, and facilitating Decision making.
3. Processes of establishment of data provenance on blockchain-based DT	- First step: data collection, Second step: data tagging, Third step: data validation, Forth step: data processing and storage, Fifth step: usage for prediction purposes.
4. The structure of required dynamic data for implementing on blockchain platform	- Tagged data or data passports on assets like location, status, time of installation, the way of installation, the organization who installed, and how it is been working during its lifetime. - Proper strategy for sync data continuously and keeping blockchain up to date. - The structure of required data containing, event log of validation and history of decisions and maintenance, and predictive models.

5. Organization of data provenance for utilizing in different aspects	- Creation of a model that is scalable, interoperable, and composable for representing assets in 3D. - Metadata management, conducting data audits, data visualization, traceability, and validation.
6. Potential benefits of data provenance on blockchain-based DT	- Data manipulation avoidance. - The synergies between blocks of blockchain providing the reliability to eliminate the third parties from the scene. - Increasing of data quality and traceability, data structuring and visualisation.
7. Challenges and prerequisites for implementation of data provenance on blockchain-based DT	- Time and cost for implementing blockchain. - No cooperating and competing IT suppliers. - No full implementation in data synchronization infrastructure. - Data volume, and integration of them from various resources.

C. Development of an ontology-based asset information model for predictive maintenance in building facilities

Interviews

Semi-structured interviews were conducted with eight industry experts (Table 5) to investigate the development of an ontology-based Asset Information Model (AIM) for predictive maintenance in building facilities. Each online interview lasted approximately **40 minutes** and explored six principal topics:

1. Existing ontologies in building facilities that can be adapted for predictive maintenance.
2. Limitations arising from the absence of common data structures and ontologies for predictive maintenance.
3. Development of an ontology-based AIM specifically designed for predictive maintenance.
4. Integration of Digital Twin technology into Asset Management.
5. Development of ontology models based on an office building case study in Stockholm.
6. Evaluation of ontology-based AIMs for predictive maintenance strategies.

Table 5. Interviewees Background

Respondent	Area of Expertise	Expertise	Country
R1	Artificial Intelligence (AI), Machine Learning (ML), and Data Analytics	25 Years	Turkey
R2	Process Manager / BIM Coordinator	4 Years	Sweden
R3	Digitization and Sustainability Specialist	10 Years	Sweden
R4	Digital Transformation and Innovation	15 Years	Denmark
R5	Business Development Director - FAIR Data	10 Years	Denmark
R6	Digital Transformation Expert - IoT, Machine Learning, Digital Twins	20 Years	USA
R7	Facility Manager Chief Engineer	32 Years	Mexico
R8	Data Engineer	6 Years	Mexico

Thematic Analysis

The semi-structured interview format enabled detailed exploration of each research topic. Following transcription, the interview data were analysed and organized into themes using NVivo. The findings, summarized in Table 6, identified eight major themes reflecting the key insights obtained from the expert interviews.

The first two themes describe alternative methodologies for ontology development, namely the conventional process-based approach and an AI-driven approach. The AI-based methodology consists of three main stages: (i) identifying an appropriate corpus of domain knowledge sources, including scientific publications, technical reports, white papers, and websites; (ii) manually annotating key entities and relationships; and (iii) applying Named Entity Recognition (NER) and Relation Extraction (RE) techniques to automate ontology development.

The third theme highlights that predictive maintenance in building facilities remains a broad research domain, emphasizing the need to define more specialized ontology classes. The interviews identified several essential ontology classes, including asset definitions, service life expectancy, maintenance activities, maintenance intervals, maintenance duration, maintenance costs, maintenance personnel, sensor data, measurement units, and data acquisition frequency.

The fourth theme establishes recommendations for ontology modelling within the building facility domain, while the fifth identifies the principal benefits of ontology-based approaches, including improved data standardization, increased automation, enhanced data-driven maintenance, reduced manual processing, and improved Machine Learning (ML) performance through semantic knowledge integration.

The sixth theme discusses implementation challenges, particularly limited interoperability among heterogeneous sensor systems, the complexity of maintaining an Asset Information Model, and balancing investments in sensor technologies against the value of additional data collection.

Finally, the seventh and eighth themes provide recommendations for evaluating ontology-based data models and present practical examples of developing ontology-based Asset Information Models for predictive maintenance applications.

Table 6. Interviews Results.

Theme	Description	Respondent
Process-based Approach	**1.** Prior to ontology development, define competency questions. **2.** Reuse existing ontologies, identify and develop the missing pieces of the established context, interview domain experts, and prioritize development of modelling guidelines. **3.** The ontology can be broken down into different cores, such modular approach enables targeting different end users in various contexts.	R3-R6
AI-based Approach	**Overview:** Employ NLP algorithms, through NER and RE techniques. Include LLM to ease NER and RE. **Process:** Define corpus of data sources (articles, white papers, websites). Perform manual annotations of entities and relations. Apply automated extraction from the predefined corpus employing NER and RE. **Tool(s):** Open-source platform that encompasses software packages supporting NER, RE, and LLM, along with annotation tools (e.g., spaCy IO).	R1

Classes and Data Hierarchy	Hierarchies and classes depend on the context. Predictive maintenance in building facilities still encompasses a broad scope, emphasizing the need for a more specific and well-defined purpose. Nevertheless, modelling guidelines and classes needed for predictive maintenance were identified and are mentioned below. Modelling Guidelines: - The main classes include Systems, Component/Object Types, and Materials. - In diagnostics, it is crucial to link sensors to geometry, establish their relationship with BIM models, and understand their spatial context and specific measurements. Automation is desirable for efficient implementation. Classes gathered through interviews: - Product life expectancy, equipment standard condition, defining assets, maintenance tasks, task intervals, task durations, potential costs, and staff involved. Sensor's observation, units of measurement, associated zone, data collection frequency, and sensor's specific location.	R2-R6, R8
Themes for Condition Monitoring	Components must be defined to assess system functionality (e.g., geo coordinates for water level sensors or factors influencing pipe flow for leakage detection). The ontology should be capable of defining the current state of the components, such as dual-purpose elements (e.g., a pipe in a system used for heating and cooling). | It should be capable of defining active and passive components.	R3, R5-R8
Potential Values and Benefits	Establish relationships between entities, enhancing predictive capabilities. Enables standardization and structured handling of large volumes of data. Substitution of repetitive manual tasks. Automated maintenance plan generation. Archived data accessibility throughout the building lifecycle. Data-driven maintenance implementation. A well-defined ontology and data model minimize the number of data points needed. Improve tasks and process automation. Improve supervised learning performance. Serves as a valuable means of integrating prior knowledge into predictive models.	R1-R8
Challenges of data interoperability	Integrating BIM metadata into FM systems. Numerous suppliers and building automation companies prioritizing closed environments. Sensor data structure incompatibility among different providers. AIM maintenance. Data restructuring after refurbishments. Achieving a balance between the number of sensors required for building performance analysis and the investment in data-point collectors.	R2, R4-R6
Assessment of data model	SHACL (Shapes Constraint Language) empowers the assessment of semantic data models, enabling quality evaluation. Tools like PySHACL enable generating data model quality reports using SHACL, facilitating comparisons across projects with consistent ontologies. By establishing a shape to validate model parameters (e.g., requiring occupancy sensors in meeting rooms), benchmarking new buildings against existing ones becomes possible, ensuring consistent standards. Ontology's impact on predictive power can be assessed by comparing predictive performance before and after incorporating it.	R1, R3-R6
AIM Development	Automation for relations and pattern identification. Need of linked data and knowledge graph. Methodologies for extracting information from semi-structured data and unstructured documents. IFC data exchange. **Sample Process for Existing Assets:** Photogrammetry (of exteriors), LiDAR Scans (of interiors), object classification through algorithms, 3D model build-up, model migration from 3D platform to FM platform (e.g., iTwin), BIM model enrichment with metadata (materials, products), IoT data flow connection (based on installed sensors). **AIM Platform:** A cloud-based FM platform should possess the ability to store and interact with BIM models, photogrammetric models, Point Cloud scanning, CAD drawings, and IoT data flows (e.g., iTwin). Additionally, it should automate manual inputs like maintenance documentation, semi-structured data, and unstructured documents.	R3, R6, R8

AI-based def: NLP: Natural Language Processing, NER: Named Entity Recognition, RE: Relation Extraction. LLM: Large Language Models

3.1.3.1.2 Quantitative Data

Questionnaire Survey

A structured digital questionnaire was developed based on the literature review. The survey design was informed by the work of Heaton and Parlikad (2020), Becerik-Gerber et

al. (2012), and Lukesh et al. (2021) and organized around three principal information categories:

- Core data
- Static Operation and Maintenance (O&M) data
- Dynamic Operation and Maintenance (O&M) data

These data categories are discussed in greater detail in the subsequent discussion section. The questionnaire employed a five-point Likert scale (Likert, 1932) to assess respondents' perceptions regarding these data categories. In addition, respondents completed multiple-choice questions that associated the principal Blockchain Technology (BCT) attributes with the different asset information categories. Each question also included open-ended response fields to collect complementary qualitative insights.

The survey was distributed through email and LinkedIn to 425 professionals, resulting in 59 valid responses, corresponding to a 14% response rate. The demographic characteristics of the respondents are summarized in Table 7.

Table 7. Questionnaire respondents: Overview

Company Type	Digitalization Consultancy: 54,2%	Asset/Facility Management: 10,2%	Real Estate Company: 6,8%	Software Company: 20,3%	Other: 8,5%
Role	Digital Twin: 3,4% Digitalization: 11,9% BIM: 8,4% AM/FM: 3,4% Company Management: 27,1%	Digitalization: 3,4% BIM: 1,7% Company Management: 5,1%	Digitalization: 5,1% Company Management: 1,7%	Consultant: 8,5% Company Management: 11,8%	Academic: 3,4% Company Management: 5,1%
Company Size					
Small (30,5%)	18,6%	1,7%	1,7%	6,8%	1,7%
Medium (30,5%)	15,3%	3,4%	0,0%	8,4%	3,4%
Large (39%)	20,3%	5,1%	5,1%	5,1%	3,4%
Operating Region					
Scandinavia (22%)	10,1%	6,8%	1,7%	1,7%	1,7%
Europe (40,6%)	22,0%	1,7%	1,7%	11,8%	3,4%
N. America (15,3%)	8,5%	0%	1,7%	3,4%	1,7%
Asia (6,8%)	3,4%	1,7%	0%	1,7%	0%
Middle East (3,4%)	1,7%	0%	1,7%	0%	0%
Oceania (11,9%)	8,5%	0%	0%	1,7%	1,7%

The statistical analysis presented in Table 8 indicates that respondents reported substantially greater expertise in Digital Twins (DT) and Asset Management (AM) than in Blockchain Technology (BCT). The relatively low standard deviations demonstrate a consistent level of expertise among participants across these three domains. The findings further reveal broad agreement that construction industry data remain highly unstructured, and that organizing and standardizing these data continue to represent major challenges.

The respondents also agreed that as-built BIM models predominantly contain geometric information while frequently lacking important asset-specific engineering information, including equipment specifications, operational characteristics, maintenance information, and manufacturer documentation.

Table 9 summarizes the perceived difficulties associated with defining, delivering, and maintaining the three principal data categories (core data, static O&M data, and dynamic O&M data). The results indicate that maintaining asset information throughout the asset life cycle represents the greatest challenge, whereas defining and delivering the information, although still demanding, are perceived as comparatively less difficult.

The relationships between respondents' expertise levels and the perceived complexity of managing the different data categories are presented in Table 10. Participants were also asked to associate each data category with one of five principal attributes of Blockchain Technology:

- Immutability
- Security
- Traceability
- Accountability
- Accessibility

The results demonstrate that traceability, particularly for dynamic O&M data, is considered the most valuable blockchain capability. Furthermore, respondents indicated that dynamic Operation and Maintenance data benefit most strongly from all five blockchain attributes, highlighting the importance of blockchain-enabled data management for real-time asset monitoring and predictive Asset Management.

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Table 8. General Statements

Questionnaire Statement	**Mn[1]**	**Md[2]**	**SD[3]**
Level of expertise regarding the concept of Digital Twin (Novice 1-10 Expert)	8,17	8	1,544
Level of expertise regarding the concept of Blockchain (Novice 1-10 Expert)	5,14	5	2,161
Level of expertise regarding the concept of Asset Management (Novice 1-10 Expert)	7,97	8	1,956
5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree)			
When working with Asset Information Requirements what the client wants is normally clear and specified.	2,39	2	1,051
When I am working with Asset Information Requirements the goals they are supposed to fulfill are clear.	3,07	3	1,096
The more granular/detail/specific the information requirement is the more problematic it becomes to define, deliver, and maintain throughout the life cycle of an asset.	2,88	3	1,366
The necessary information and data for Operation and Maintenance/Facility Management is usually transferred from the construction and design phase to the operational phase.	2,46	2	1,222
As-built BIM models usually only contains as-built geometry but lacks asset specific engineering data (e.g., detailed performance specifications and manufacturer data).	3,76	4	1,088
.ifc (Industry Foundation Classes) is an appropriate file format to use as the virtual representation of a physical asset in the context of a digital twin.	3,12	3	1,068
Data collected in the construction industry is usually unstructured.	3,86	4	0,918
It is challenging to structure the data collected in the construction industry.	3,59	4	1,219

[1]Mean, [2]Median, [3]Standard Deviation

Table 9. Key Data Categories - Define, Deliver, Maintain

	Core Data		Static OM Data		Dynamic OM Data		Average	
	Mean	SD[1]	Mean	SD[1]	Mean	SD[1]	Mean	SD[1]
Define	2,15	0,997	2,52	1,017	2,33	1,223	2,34	1,079
Deliver	2,53	0,912	2,74	0,925	2,59	1,135	2,62	0,991
Maintain	3,07	1,060	3,30	0,974	2,88	1,236	3,08	1,090
Average	2,58	0,990	2,85	0,972	2,60	1,198	2,68	1,053

[1]Standard Deviation

Table 10. Spearman's Rank Correlation (Spearman, 1904) between graded level of expertise and defining, delivering, and maintaining the three Key Data Categories

	Level of Expertise			Core Data			Static OM Data			Dynamic OM Data		
	DT	BCT	AM	Define	Deliver	Maintain	Define	Deliver	Maintain	Define	Deliver	Maintain
DT	1,000	0,356**	0,521**	-0,241	0,022	0,082	-0,255	-0,384**	-0,219	-0,160	-0,189	-0,054
BCT	0,356**	1,00	0,214	0,106	0,199	0,172	-0,020	-0,093	-0,004	0,037	0,025	0,119
AM	0,521**	0,214	1,000	-0,098	-0,055	-0,009	-0,069	-0,199	-0,185	0,061	0,058	0,180

**. Correlation is significant at the 0.01 level (2-tailed)

3.2 Analytics and modeling of processes for the Blockchain-based DT System

3.2.1 Ontology Development

The ontology developed for this case study was adapted from the BrickSchema and RealEstateCore (REC) ontologies and implemented using the Ontology Development 101 (OD1) methodology within the Protégé ontology development environment (Siricharoen, 2018). The ontology development process followed a systematic knowledge engineering approach, beginning with the collection and analysis of asset information from the Pythagoras AB building. Relevant domain concepts, entities, and relationships were identified and mapped to existing classes and subclasses defined in the BrickSchema and RealEstateCore ontologies to maximize semantic interoperability and reuse.

In addition to the existing ontology structures, concepts and requirements identified through the expert interviews were incorporated into the ontology by introducing new classes, object properties, data properties, and semantic relationships within the Protégé platform. This iterative process enabled the ontology to capture the information required to support Asset Information Models (AIMs), Digital Twins (DTs), and predictive maintenance applications in building facilities. The resulting ontology provides a semantically structured knowledge model that facilitates standardized information representation, interoperability, and intelligent data integration across building management systems.

Table 11 summarizes the complete ontology development process based on the Ontology Development 101 (OD1) methodology. Figure 4 illustrates the hierarchical structure of the resulting ontology classes, while Figure 5 presents the corresponding WebVOWL visualization, highlighting the semantic relationships among the ontology concepts. A comprehensive description of the ontology, including its conceptual model, class hierarchy, and implementation details, is provided by Gispert et al. (2023).

Table 11. Ontology Development according to OD1 Method

Step	**Results**
Determine the domain and scope of the ontology:	Domain: Predictive Maintenance in Building Facilities Scope: Ontology-based Asset Information Model for Predictive Maintenance
Consider reusing existing ontologies:	From BOT alignment modules: BrickSchema and Real Estate Core (REC)
*Enumerate important terms in the ontology:	Conference Room, Occupancy Sensor, Temperature Sensor, Air Quality Sensor, AV Equipment, Window, CO2 Level, Lightning Level, Power Usage
Define the classes and hierarchy:	Constructed from BrickSchema and REC Ontologies for Stockholm's conference room case study: • Equipment - Electrical Equipment (has 4 subclasses)** - Fire Safety Equipment (has 3 subclasses) - HVAC Equipment (has 4 subclasses) - Lightning Equipment (has 1 subclass with 2 subclasses) - Safety Equipment (has 2 subclasses) - Shading Equipment (has 1 subclass) • Location - Building - Floor - Space (has 1 subclass with 1 subclass)

	- Zone (has 2 subclasses) • Point - Alarm (has 3 subclasses) - Sensor (has 6 subclasses) - Setpoint (has 3 subclasses) - Status (has 1 subclass) Concepts added, gathered through interviews: Life expectancy, standard condition, assets definition, maintenance task, task interval, task duration, potential costs, and staff involved.

*Terms collected based on Stockholm's conference room case study

**See Figure 3 for the depiction of classes and subclasses

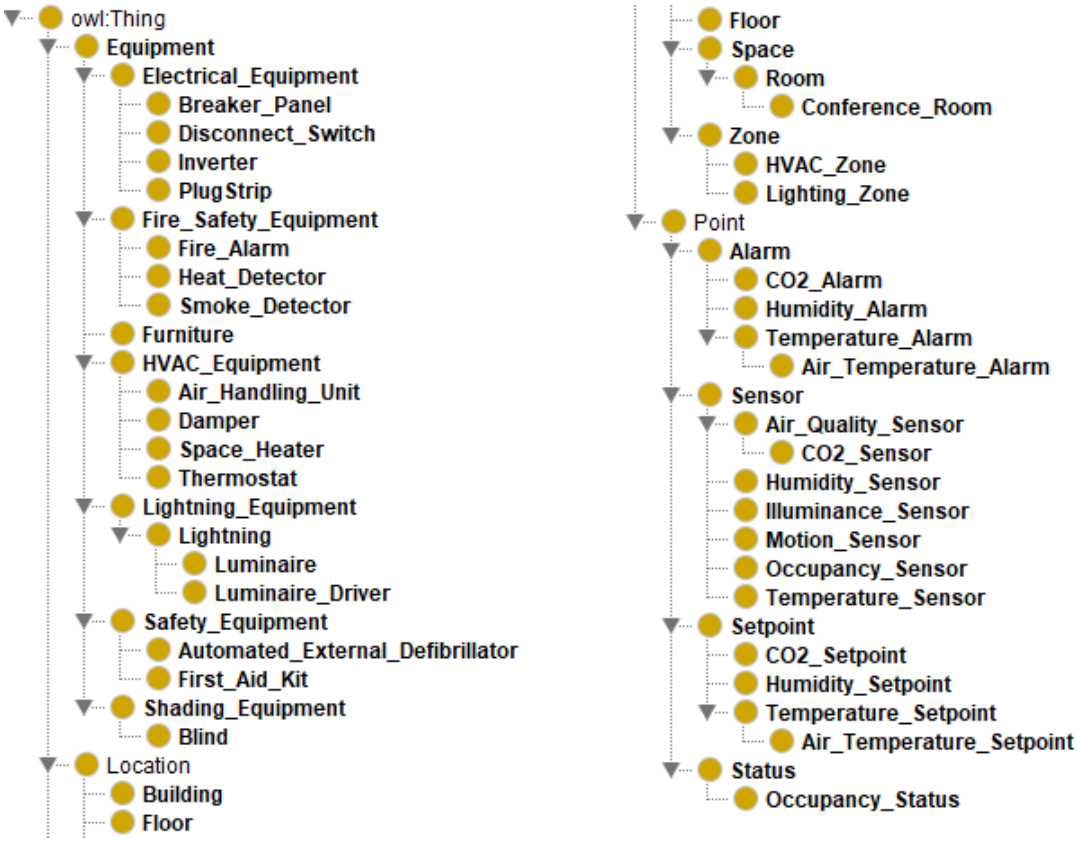

Figure 4. Ontology Classes shown in Protégé Environment (Gispert et al., 2023)

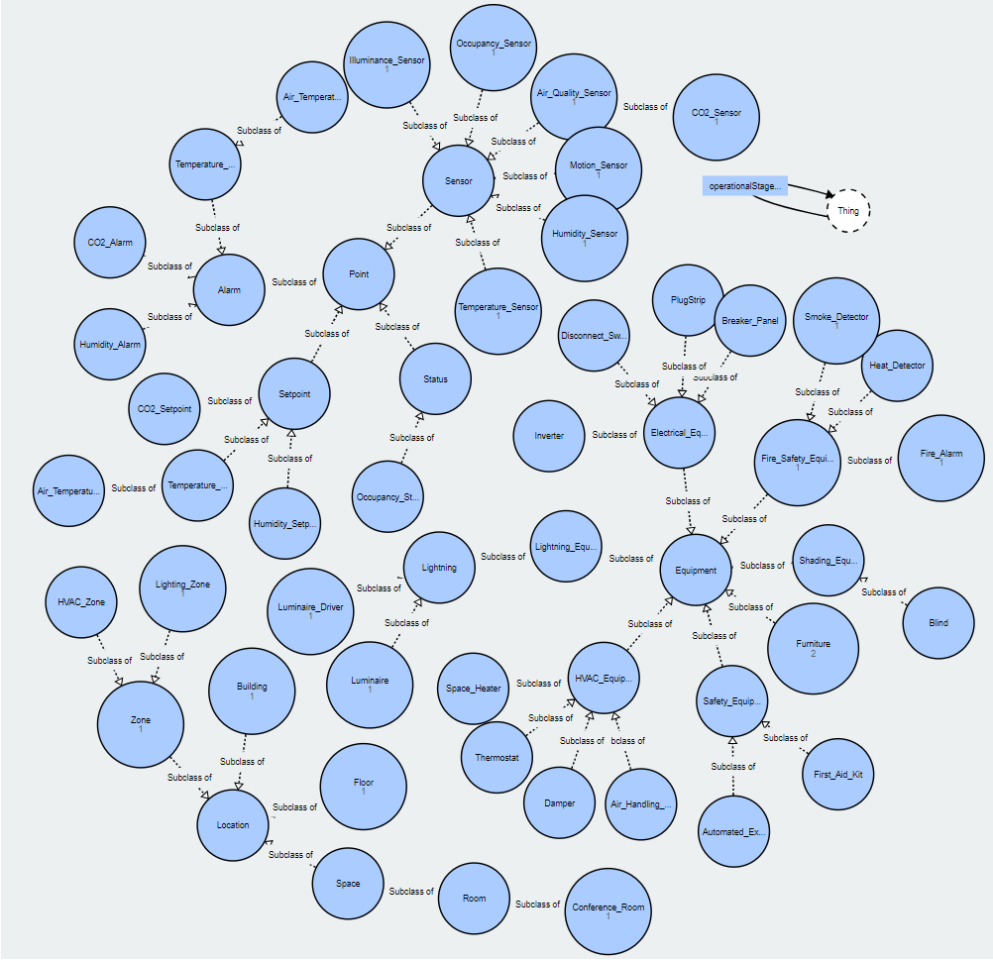

Figure 3. Ontology Representation using WebVOWL (Gispert et al., 2023).

3.2.2 Entity relationships in ontology

In the development of an ontology-based Asset Information Model (AIM) for predictive maintenance in building facilities, defining the relationships and connections between entities is fundamental for establishing a structured, semantically rich representation of asset information and domain knowledge. A comprehensive ontology for predictive maintenance should encompass a broad range of entities, including building components (e.g., HVAC systems, alarms, and sensors), maintenance activities (e.g., inspections, servicing, and repairs), environmental conditions (e.g., temperature, humidity, and CO_2 concentration), and sensor-generated operational data. The effectiveness of predictive maintenance largely depends on accurately defined semantic relationships that capture the cause-and-effect interactions among these entities (Canito et al., 2022). For example, an ontology should be capable of linking potential failures of an HVAC system to preceding environmental conditions, sensor observations, or historical maintenance activities, thereby supporting root-cause analysis, condition assessment, and reliable failure prediction.

From an interoperability perspective, predictive maintenance requires the integration of heterogeneous information sources, including IoT sensor data, maintenance records, Asset Information Models (AIMs), and environmental monitoring systems. Clearly defined semantic relationships enable seamless data interoperability among these diverse data sources by providing a common conceptual framework for information exchange. Consequently, the ontology functions as a standardized semantic model that eliminates data silos and facilitates comprehensive analysis across multiple systems and platforms. In addition, semantic relationships enhance the contextual interpretation of information by explicitly describing how entities are interconnected. For instance, linking a sensor observation to the health condition of a specific building component enables more meaningful interpretation of operational data and supports more accurate maintenance decision-making (Cao et al., 2020).

Well-defined entity relationships are equally important for ensuring the scalability and long-term maintainability of ontology-based systems. As additional data sources, building assets, maintenance activities, and operational processes are incorporated into the system, consistent and unambiguous semantic relationships enable efficient expansion without compromising data quality or system performance. Furthermore, structured relationships facilitate knowledge transfer by enabling both ontology developers and intelligent software applications to capture, reuse, and reason over domain expertise. This capability is particularly important for supporting automated reasoning, intelligent maintenance planning, and data-driven decision-making in Asset Information Models (AIMs) for building facilities (Von Enzberg et al., 2020).

Figure 6 presents an overview of the processes involved in the implementation of the ontology-based Asset Information Model (AIM), illustrating how ontology entities, semantic relationships, sensor data, maintenance information, and predictive maintenance workflows are integrated to support intelligent asset management and decision support.

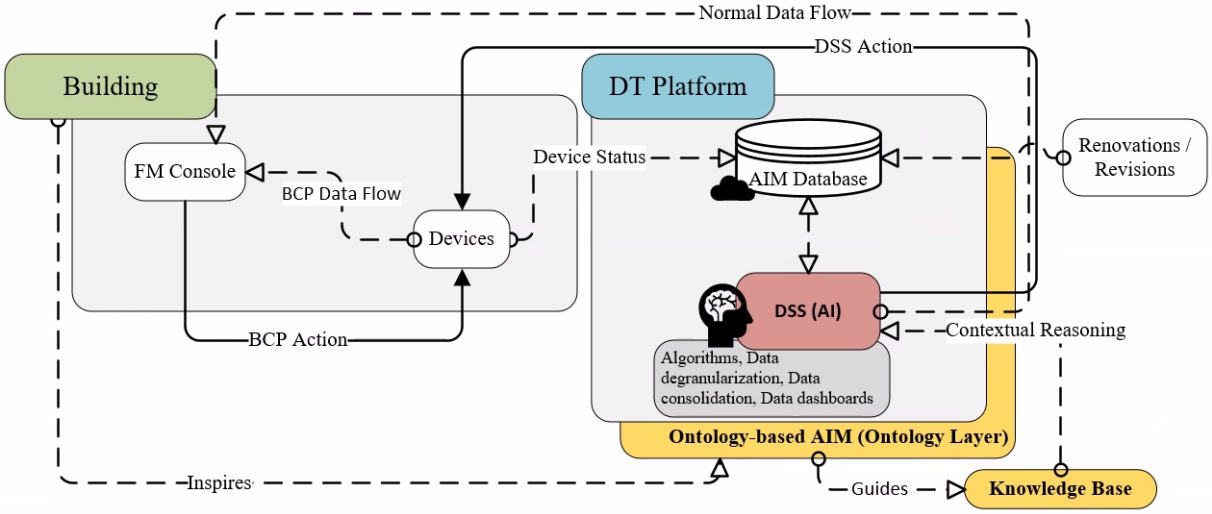

Figure 6. Ontology-based AIM for Predictive Maintenance in Building Facilities Framework (Gispert et al., 2023)

3.2.3 Functional Model using IDEF0

3.2.3.1 The overarching view and the components

This research adopts the IDEF0 methodology to develop a functional model for a Blockchain-based Digital Twin (DT) framework that supports smart, secure, and intelligent Asset Management. Figure 7 presents the overall functional model, illustrating the primary function (Node A0) together with its Input, Control, Output, and Mechanism (ICOM) representation. The proposed framework is designed to establish an integrated digital environment for Asset Lifecycle Management (ALM) by combining as-built Building Information Models (BIM) with real-time operational data acquired from Internet of Things (IoT) devices, sensors, and maintenance management systems. These information sources provide the foundation for continuous monitoring, predictive analysis, and intelligent decision support throughout the building life cycle.

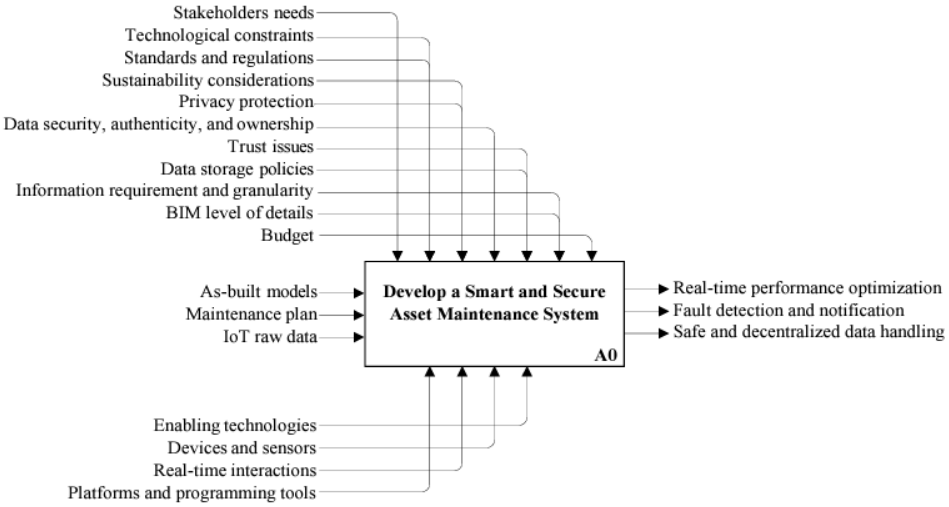

Figure 7. The primary function, overviewing the framework development requirements (Sadri et al., 2023).

Within the proposed framework, maintenance strategies play a critical role in planning maintenance activities, monitoring asset performance, scheduling interventions, and minimizing unexpected failures, operational disruptions, emergency repairs, and lifecycle costs. By supporting predictive maintenance, condition monitoring, and proactive asset management, the framework contributes to improved operational efficiency, extended asset service life, enhanced building performance, and increased user satisfaction (Assaf and Srour, 2021). Furthermore, the Blockchain-based Digital Twin provides a secure and trustworthy environment for managing asset information, enabling real-time monitoring, autonomous fault detection, predictive notifications, and intelligent asset performance optimization.

The framework integrates a wide range of disruptive digital technologies, including Blockchain Technology, Digital Twins, Building Information Modeling (BIM), Internet of Things (IoT), software platforms, programming languages, communication technologies, sensors, and hardware devices to support data acquisition, processing, storage, analysis, and visualization. The development process is driven by the intended use cases and is

informed by stakeholder requirements, Asset Information Requirements (AIR), Organizational Information Requirements (OIR), and the required Level of Information Need within the BIM environment. Additional considerations—including funding availability, regulatory compliance, sustainability objectives, cybersecurity, data privacy, and information sensitivity—also influence the system architecture and define appropriate data governance and information management protocols.

Within the hierarchical IDEF0 structure, the parent function (Node A0) is decomposed into four primary sub-functions that collectively define the architecture of the proposed Blockchain-based Digital Twin framework:

- A01 – Equipping the Physical Entity
- A02 – Constructing the Digital Twin
- A03 – Integrating Blockchain with the Digital Twin
- A04 – Developing the User Interface

These sub-functions, illustrated in Figure 7, represent the principal functional components of the proposed framework. A more detailed decomposition of Nodes A02 and A03 further describes the processes involved in developing the Digital Twin, integrating Blockchain Technology, enabling secure information exchange, supporting intelligent analytics, and establishing a trusted digital ecosystem for smart Asset Lifecycle Management (ALM).

3.2.3.2 Decomposition of the DT development function

Figure 6 illustrates the decomposition of Node A02, representing the Digital Twin (DT) development function, into four primary sub-functions: data acquisition (A021), data processing (A022), model and algorithm development (A023), and analysis and control (A024). The development process is driven by two principal inputs—as-built Building Information Models (BIM) and real-time data collected from Internet of Things (IoT) devices and sensors. These inputs undergo a sequence of structured processes that culminate in the creation of a high-fidelity Digital Twin, enabling continuous asset monitoring, automated fault detection, intelligent notifications, predictive analytics, and real-time optimization of building performance through well-defined control mechanisms.

Within the built environment, the capability to respond to dynamic changes in asset conditions is essential for ensuring the resilience and effectiveness of automated sensing and monitoring systems. Recent advances in Internet of Things (IoT) technologies have introduced a new generation of intelligent devices capable of sensing, identification, communication, and real-time data exchange across a wide range of building and facility systems (A. Verma et al., 2021). Previous studies have demonstrated that IoT devices are typically designed for application-specific purposes, with sensor selection determined by the need to collect accurate and reliable measurements for predefined operational parameters (Gao et al., 2021). Furthermore, the deployment of 5G communication networks has significantly improved the reliability, responsiveness, bandwidth, and scalability of IoT-enabled monitoring systems, thereby enhancing the performance of connected Digital Twin environments.

The continuous operation of smart devices and IoT sensors generate substantial volumes of heterogeneous Big Data, making manual data processing impractical and computationally inefficient (Wang et al., 2022). Consequently, advanced computational techniques and cognitive data processing methods are required to cleanse, validate, align, integrate, and transform raw sensor data into structured information suitable for Digital

Twin applications. In this context, ontologies and Knowledge Graphs (KGs) provide powerful semantic frameworks for organizing heterogeneous information and enriching Building Digital Twins through explicit semantic relationships among assets, systems, sensors, maintenance activities, and operational events (Xia et al., 2022). By representing domain knowledge as interconnected semantic entities and relationships, Knowledge Graphs facilitate automated reasoning, support root-cause analysis, identify abnormal system behavior, and enable proactive responses to emerging operational issues. These semantic approaches also address interoperability limitations within IoT ecosystems by supporting pattern recognition, anomaly detection, and predictive analytics using data acquired from distributed IoT devices and sensors (Chanal et al., 2021).

In addition, Artificial Intelligence (AI) and Machine Learning (ML) further enhance the capabilities of the Digital Twin by enabling predictive maintenance, improving operational decision-making, optimizing maintenance planning, reducing operational risks, and supporting more accurate cost estimation during the Operation and Maintenance (O&M) phase of building facilities (Regona et al., 2022). Together, these technologies establish an intelligent Digital Twin ecosystem capable of delivering continuous monitoring, advanced analytics, and autonomous decision support throughout the asset life cycle.

3.2.3.3 Blockchain Integration Function Breakdown

Figure 4 presents the decomposition of Node A03, illustrating the Blockchain integration function within the proposed Blockchain-based Digital Twin framework. The process is divided into three principal sub-functions: organizing data (A031), storing raw data off-chain (A032), and storing processed data on-chain (A033). Together, these interconnected functions establish a secure and scalable data management architecture that supports the Digital Twin by classifying, validating, storing, and managing asset information across both on-chain and off-chain environments.

Data management in Blockchain-based systems generally relies on a hybrid architecture that combines on-chain and off-chain storage mechanisms to balance security, scalability, performance, and cost efficiency. On-chain storage records critical transactions, metadata, asset identifiers, digital signatures, and verification records directly on the blockchain ledger. Every recorded transaction contributes to updating the blockchain state, thereby ensuring immutability, data integrity, traceability, transparency, and secure verification of asset information throughout the Asset Lifecycle Management (ALM) process.

In contrast, off-chain storage manages large volumes of operational information—including sensor measurements, Building Information Models (BIM), maintenance documentation, images, videos, and other high-volume datasets—within external databases, distributed file systems, or cloud storage platforms. This approach significantly improves system scalability and processing efficiency while reducing blockchain storage requirements and transaction costs. Cryptographic hashes and references stored on-chain maintain secure links to the corresponding off-chain data, ensuring that information remains verifiable, tamper-resistant, and synchronized between the blockchain and the Digital Twin platform. The integration of on-chain and off-chain storage therefore provides an efficient, secure, and interoperable foundation for trusted data management, intelligent analytics, and smart Asset Lifecycle Management.

3.3 Blockchain-based DT System Platform

3.3.1 Deployment of smart contract

Use Case 1 focuses on the development of a Blockchain-based Digital Twin (DT) platform that securely stores critical Digital Twin information—including IoT sensor data—on the blockchain to support Predictive Asset Maintenance (PAM) and enable continuous assessment of asset conditions through smart contracts. The smart contract was developed using Solidity within the Remix Ethereum Integrated Development Environment (IDE) (Figure 9). Following development, the contract was compiled using the Solidity compiler and deployed through the Remix platform using MetaMask's Injected Provider as the execution environment. During deployment, MetaMask, a web-based cryptocurrency wallet, prompts the user to review and authorize the blockchain transaction before the smart contract is published to the network (Celik et al., 2023).

After successful deployment on the Sepolia testnet (Fernandes and Werner, 2023), the blockchain transaction can be verified through Etherscan, a widely used Ethereum blockchain explorer. Etherscan provides comprehensive transaction metadata, including the transaction hash, transaction status (successful or failed), block number containing the transaction, timestamp, smart contract addresses, gas consumption, and transaction fees, thereby ensuring complete transparency, traceability, and verification of blockchain operations (Figure 10).

To enable seamless communication between the smart contract and the application layer, an Application Programming Interface (API) was developed using JavaScript and the Express framework. The server acts as an intermediary between the blockchain, the front-end application, and the user interface, facilitating secure interaction with the deployed smart contract. The API provides three principal functions: "Connect to MetaMask," "Connect to Contract," and "Get Data from Contract," enabling authenticated users to establish blockchain connections, access the deployed smart contract, and retrieve stored asset information. Furthermore, the Index.html application incorporates the Application Binary Interface (ABI) together with the deployed smart contract address (contract hash) generated in Remix Ethereum, allowing the web interface to invoke smart contract functions and interact with the Ethereum Virtual Machine (EVM) through the blockchain network.

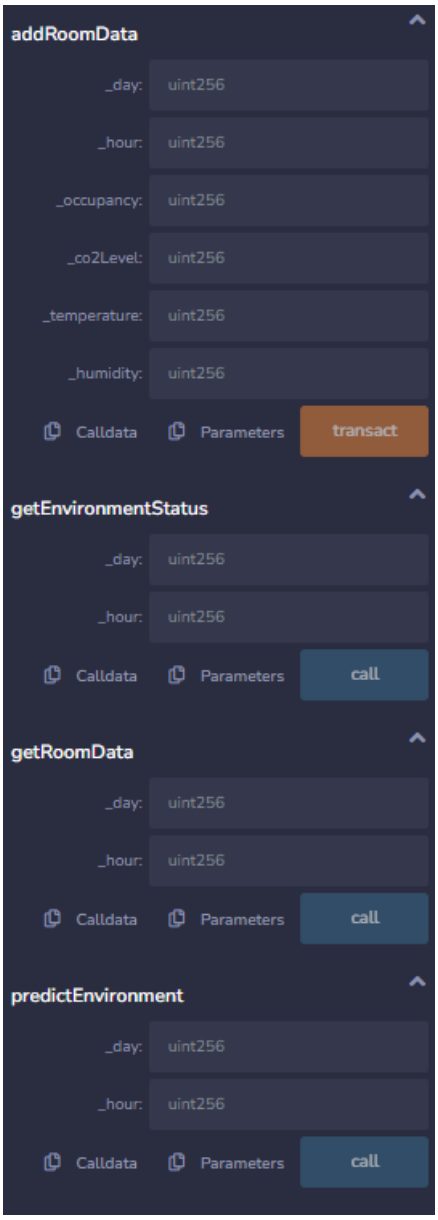

Figure 8. Add room data and retrieve functions.

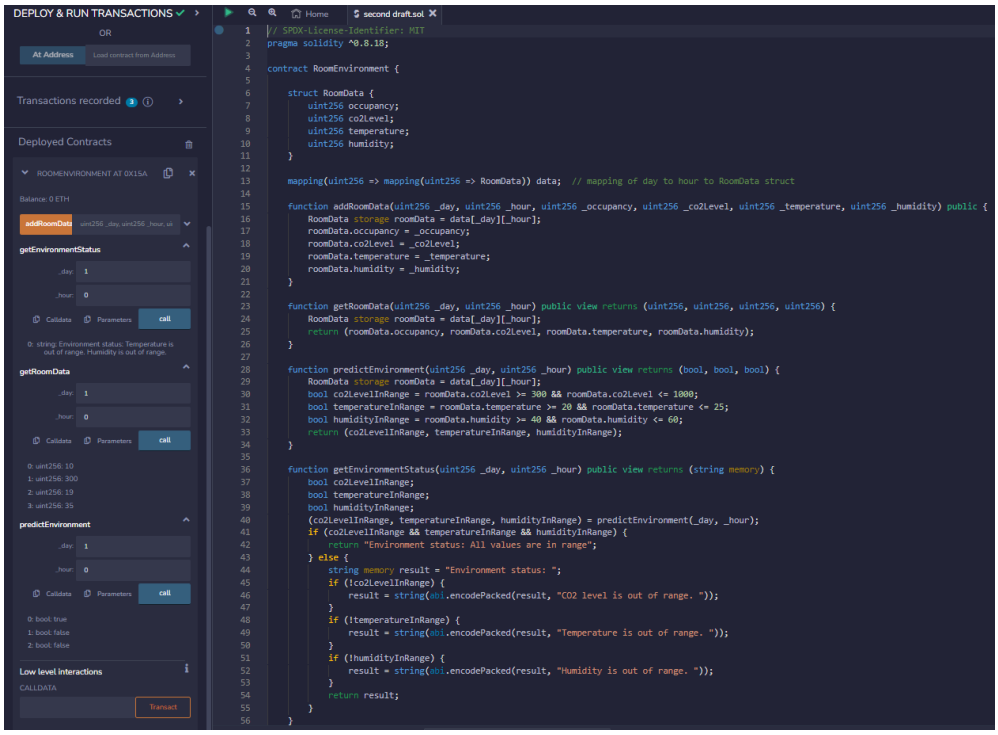

Figure 9. Smart contract using Remix Ethereum platform.

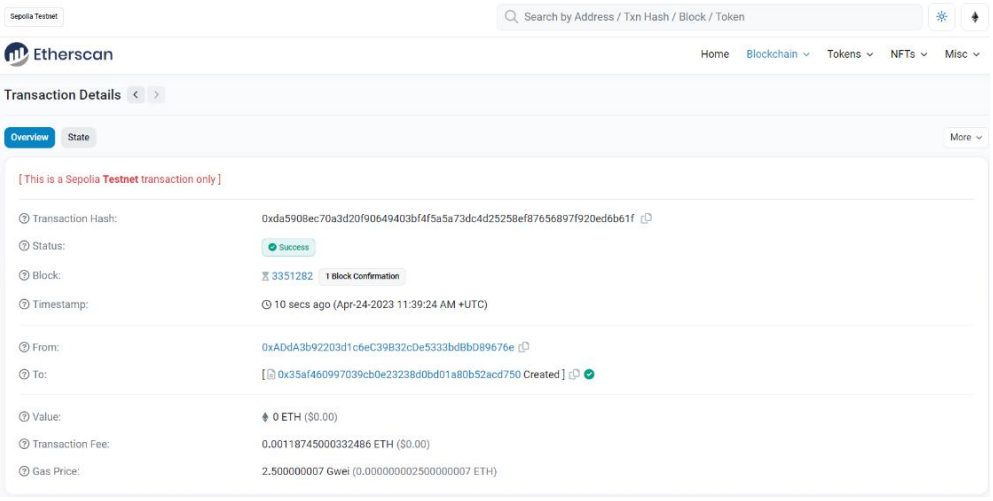

Figure 10. Etherscan transaction details.

3.3.2 Process map of blockchain implementation

Blockchain Technology (BCT) provides a decentralized, secure, and automated framework that enhances Asset Management (AM) by improving data integrity, reducing administrative complexity, minimizing process delays, and lowering operational costs. Through its distributed ledger architecture, blockchain enables transparent and immutable recording of asset-related transactions throughout the asset lifecycle, allowing facility managers to effectively monitor asset acquisition, operational status, maintenance history, repair activities, and end-of-life disposal. This comprehensive asset traceability improves asset valuation, strengthens auditability, and significantly reduces the risk of human error, data manipulation, and fraudulent activities (Ramachandran & Kantarcioglu, 2017; Sahal et al., 2021). Furthermore, Blockchain Technology supports predictive analytics by securely integrating heterogeneous data from multiple sources, enabling facility managers to develop predictive models that forecast maintenance requirements, identify potential failures at an early stage, and optimize asset utilization and operational performance.

As illustrated in Figure 11, the proposed blockchain implementation process begins with the acquisition of essential information from the Digital Twin (DT), including asset specifications, maintenance schedules, IoT sensor data, and real-time operational measurements. These datasets are securely stored within an off-chain cloud storage environment that operates in conjunction with an Artificial Intelligence (AI)-based Predictive Asset Maintenance (PAM) algorithm. Off-chain storage provides scalable and efficient management of large data volumes while maintaining secure connectivity with the blockchain network.

Following data acquisition, selected information and transaction metadata are securely transmitted to the Ethereum Virtual Machine (EVM), where smart contracts execute predefined business logic through authenticated interactions established via MetaMask. The blockchain network validates each transaction through distributed node consensus, ensuring data integrity, immutability, privacy, transparency, and decentralization throughout the information management process. Once verified, blockchain records are made accessible through decentralized applications (DApps) or Application Programming Interfaces (APIs) that provide seamless integration between the blockchain, distributed ledger, and enterprise information systems.

Using these DApps or APIs, facility managers and other authorized stakeholders can securely monitor asset conditions, access maintenance records, review operational histories, initiate maintenance workflows, and utilize advanced decision-support functions. Finally, validated maintenance activities, inspection results, and updated operational information are synchronized back to the Digital Twin, ensuring continuous bidirectional information exchange, accurate digital asset representation, and consistent data throughout the Asset Lifecycle Management (ALM) process (Tezel et al., 2020).

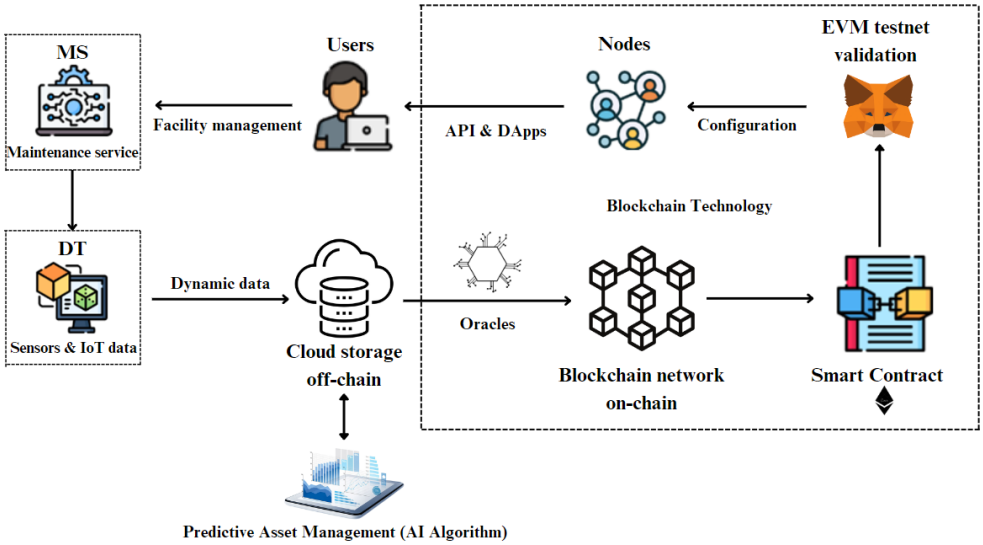

Figure 11. Implementation of Data Provenance Model on Blockchain-based DT (Tavakoli et al., 2023).

3.3.3 Establishment of required data in data provenance

The successful implementation of a Blockchain platform for Asset Management requires the establishment of a robust data provenance framework supported by several critical components. Standardization is fundamental for managing the heterogeneous and dynamic data generated throughout the blockchain ecosystem, enabling seamless deployment of smart contracts, automated workflows, and consistent information exchange across multiple systems. A well-defined data provenance strategy ensures the quality, reliability, authenticity, and traceability of asset information by incorporating structured procedures for data collection, classification, tagging, validation, and storage, thereby providing trustworthy data for predictive analytics and intelligent decision-making.

The proposed framework combines both on-chain and off-chain data management approaches to maximize the capabilities of the Blockchain-based Digital Twin platform. On-chain data, stored directly within the blockchain ledger, provides immutable, transparent, and cryptographically secure records for transaction verification, data integrity, and auditability. In contrast, off-chain data is maintained within external databases, cloud platforms, or distributed storage systems and is securely linked to the blockchain through oracles, thereby enabling efficient management of large datasets while extending the functionality and scalability of the asset management platform. Effective data synchronization mechanisms are implemented to ensure consistency and real-time alignment between on-chain records, off-chain repositories, and the Digital Twin, maintaining an accurate representation of asset status throughout the Asset Lifecycle Management (ALM) process.

Furthermore, the development of a scalable, 3D-compatible asset model enhances interoperability among Building Information Modelling (BIM), Digital Twins (DTs), Internet of Things (IoT) devices, and other enterprise information systems. Complementary mechanisms—including metadata management, data auditing, visualization tools, traceability services, and secure data governance policies—further strengthen the integrity, transparency, and reliability of blockchain-managed information. Collectively, these components establish a resilient and trustworthy asset management ecosystem that fully exploits the capabilities of Blockchain Technology while supporting intelligent decision-making, predictive maintenance, and optimized asset performance.

This research provides important contributions to Facility Management (FM) and Asset Maintenance by demonstrating how Blockchain Technology can improve the reliability and transparency of asset information throughout the building life cycle. The integration of blockchain ensures that asset records are tamper-proof, traceable, and verifiable, thereby increasing stakeholder confidence in operational and strategic decision-making. The availability of trustworthy information enables facility managers to optimize asset utilization, improve maintenance planning, and anticipate future maintenance requirements through predictive analytics, resulting in greater operational efficiency and reduced lifecycle costs. Moreover, blockchain enhances predictive maintenance by ensuring continuous data accuracy, secure real-time information exchange, and reliable synchronization between physical assets and their Digital Twins, enabling early fault detection, timely maintenance interventions, minimized operational downtime, and improved overall asset performance. Consequently, this study presents a practical and scalable framework for implementing Blockchain-based Asset Management, supporting more efficient, transparent, and intelligent management of building facilities.

3.4 User Interface- Dashboard for Indoor Environment Quality in building operations and energy management

Following the dashboard configuration, a comprehensive case study was conducted in a four-story administrative building located in Jönköping, Sweden, using three years of operational data to demonstrate the real-world capabilities of the proposed platform prototype. The platform continuously processes data collected from the building and presents the results through an interactive interface, enabling different stakeholders to access and interact with the system according to their predefined roles and access privileges. As illustrated in Figure 12, the dashboard consists of six integrated modules that collectively support intelligent building operation, Digital Twin (DT) monitoring, predictive maintenance, Blockchain integration, and sustainability assessment.

The first module, located at the top of Figure 12, provides an interactive visualization of both historical and real-time building data through dynamic line charts, allowing users to analyze information collected from IoT devices and sensors. In this case study, the module presents detailed information on energy consumption, including district heating, district cooling, and electricity consumption, together with indoor temperature measurements. The information can be explored at hourly, daily, and monthly resolutions, enabling comprehensive temporal analysis of building performance.

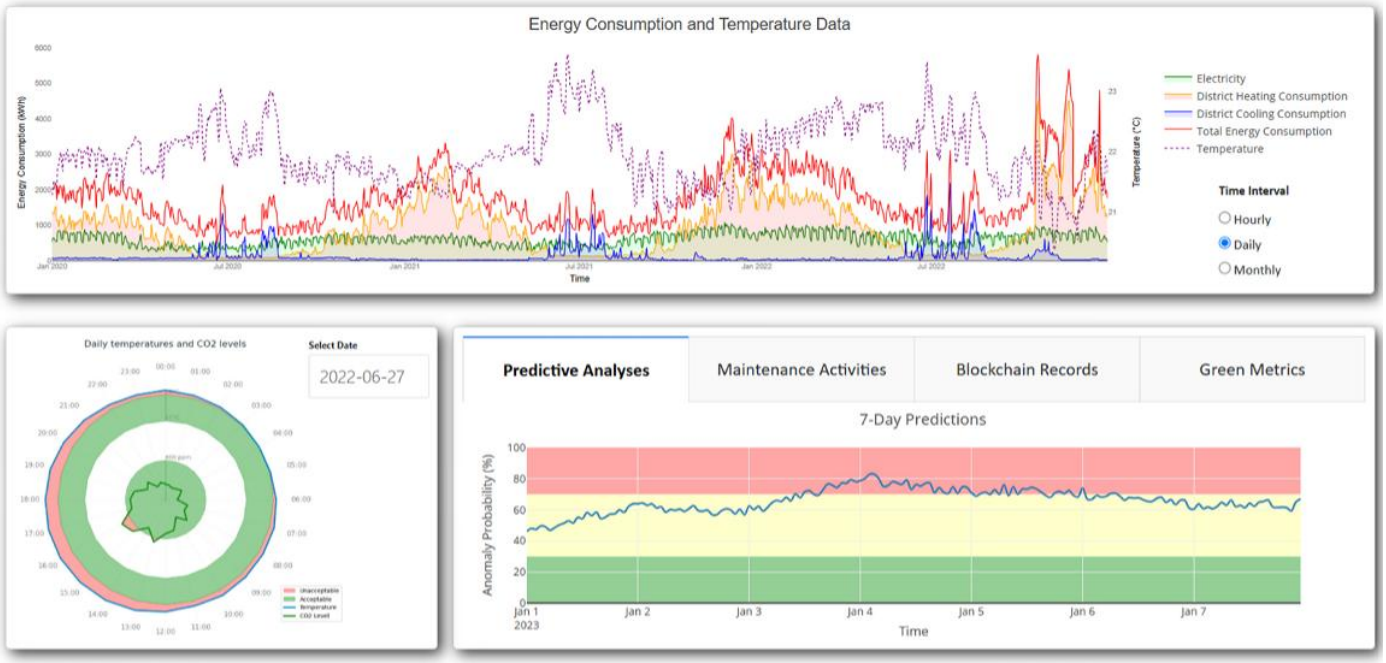

Figure 12. Overview of the Dashboard Modules for Historical and Real-Time Data, Indoor Comfort Assessment, and Advanced Analytics (Sadri, 2025).

The second module, positioned directly below the temporal visualization, evaluates indoor environmental comfort using an interactive radar chart. The radar chart illustrates acceptable operating ranges for indoor temperature and CO_2 concentration, where the

optimal conditions are represented within a designated green zone. These threshold values can be customized according to service-level agreements established between tenants and facility managers. In this study, the temperature thresholds are based on the recommendations of the Swedish Work Environment Authority, covering both normal and reinforced clothing conditions. Deviations in temperature or CO_2 concentration are highlighted in red, indicating departures from the expected performance of the HVAC system. These performance deviations are subsequently used as input for performance-based payment mechanisms, which are automatically managed through Blockchain-enabled smart contracts.

The analytics section, located adjacent to the radar chart, consists of four analytical modules organized into separate tabs that support advanced analysis of raw operational data, extraction of hidden insights, and continuous building performance monitoring. The third module, entitled Predictive Analyses, presents an interactive line chart (Figure 12) that estimates the probability of anomalies using Artificial Intelligence (AI) algorithms. The module predicts potential operational anomalies before failures occur and generates early warnings for the facility manager, enabling proactive implementation of preventive maintenance measures. These predictive outputs subsequently trigger Blockchain-enabled smart contracts, which automatically initiate appropriate maintenance workflows.

The fourth module, entitled Maintenance Activities (Figure 13), manages active maintenance cases and visualizes maintenance workflows through a sequence diagram. When the AI system identifies an anomaly based on data received from the Digital Twin, it generates an alert indicating a potential equipment failure. This event automatically activates a smart contract, which creates a maintenance request and forwards it to the facility manager for approval. After approval, the request is transmitted to the HVAC service provider. Once the service provider confirms the assignment, the smart contract automatically notifies both the facility manager and the tenant, while simultaneously reserving the required financial resources through an escrow mechanism. Following successful completion of the maintenance activity, the smart contract releases the payment and records a permanent maintenance summary on the blockchain, making the verified maintenance history accessible to authorized stakeholders.

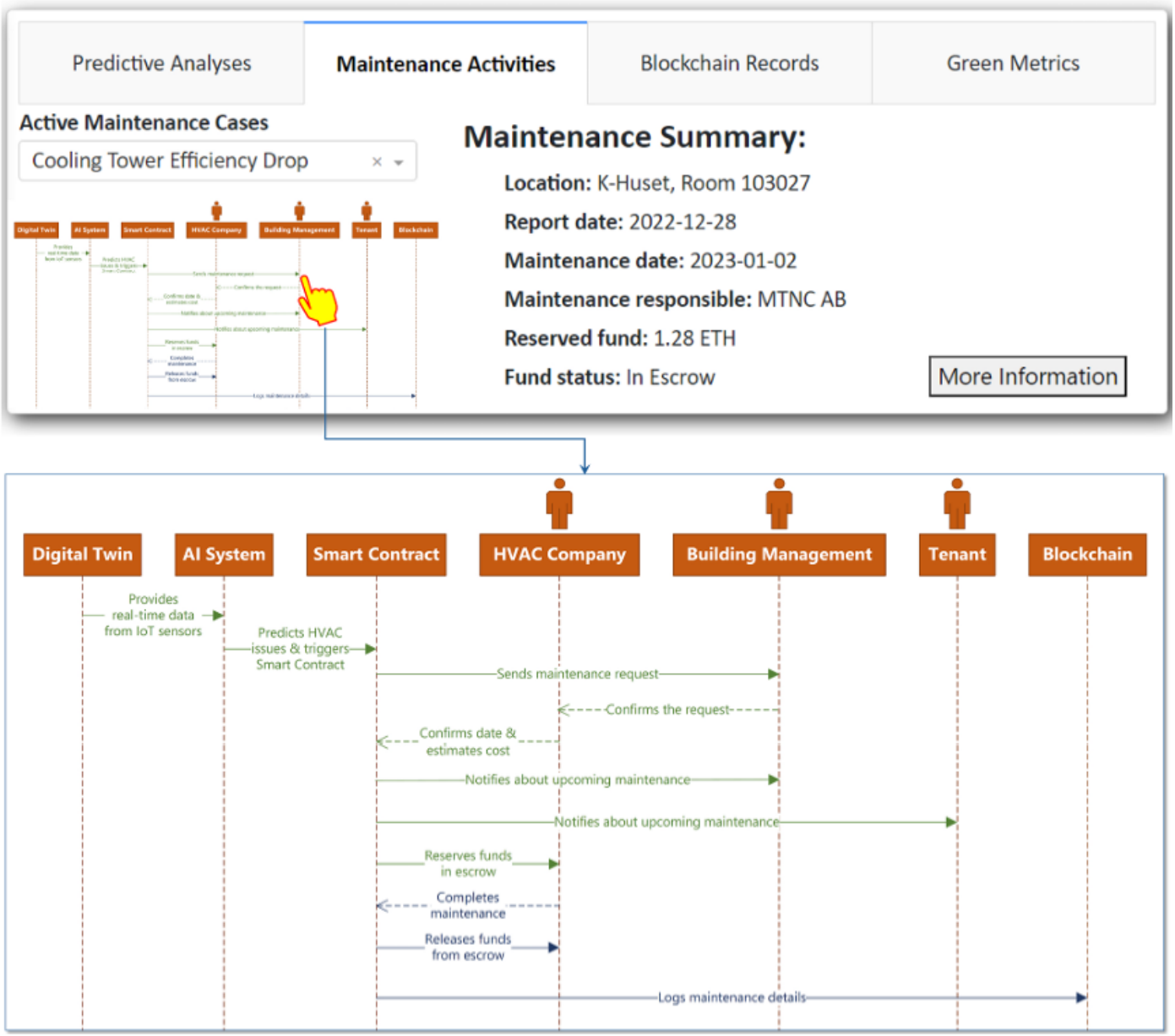

Figure 13. Overview of the Maintenance Activities Module for Monitoring Ongoing Maintenance Tasks and Associated Information (Sadri, 2025).

The fifth module, entitled Blockchain Records (Figure 14), provides a transparent representation of blockchain activities associated with building operation and maintenance. The module includes a pseudocode representation of the implemented smart contract, together with a chronological record of blockchain transactions. Each block stores essential operational information, including indoor comfort performance indicators (e.g., radar chart deviation values), AI-generated predictions, maintenance events, and payment records, together with blockchain metadata such as the unique block identifier, timestamp, hash of the previous block, and the cryptographic hash of the current block data. The

hashing mechanism encrypts and secures all blockchain records, thereby ensuring data integrity, immutability, traceability, and protection against unauthorized modification.

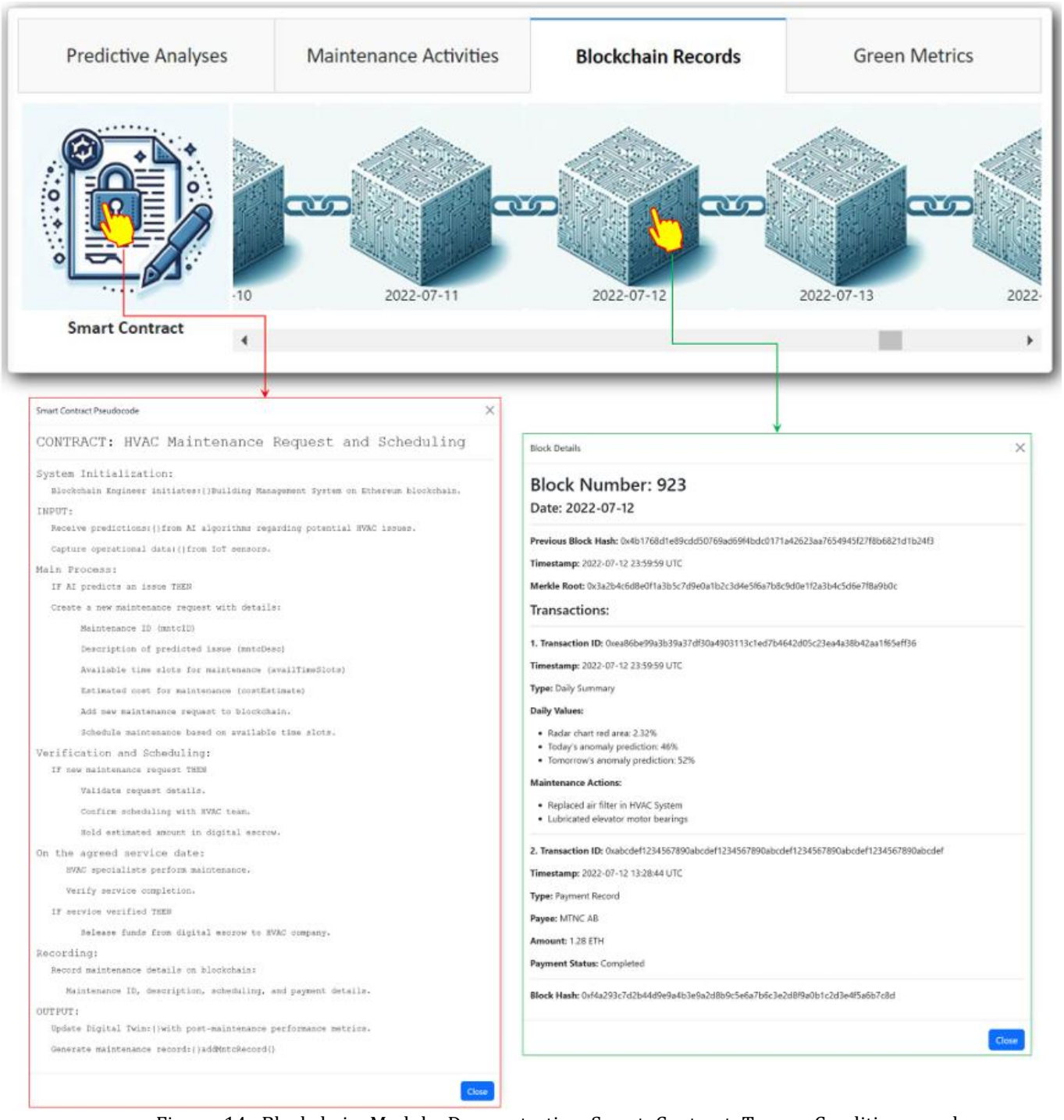

Figure 14. Blockchain Module Demonstrating Smart Contract Terms, Conditions, and Blockchain Transaction Records (Sadri, 2025).

The final module, entitled Green Metrics (Figure 15), provides a comprehensive assessment of the building's sustainability performance, with particular emphasis on its carbon footprint. The module converts energy consumption data into monthly estimates of carbon emissions and presents the results using intuitive visualizations, including pie charts and color temperature indicators. Lower energy consumption is represented by shorter columns and cooler color tones, indicating reduced carbon emissions, whereas higher consumption is associated with warmer colors, highlighting increased environmental impact. These visual representations support informed decision-making by emphasizing opportunities for energy conservation, operational optimization, and the integration of renewable energy solutions, thereby contributing to more sustainable and intelligent building management.

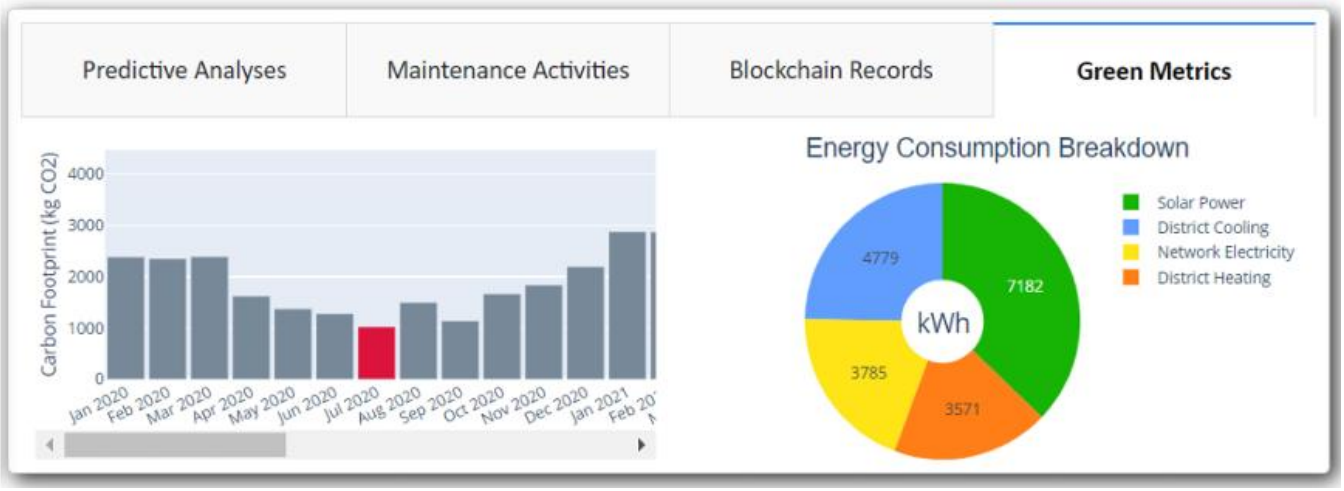

Figure 15. Green Metrics Module Illustrating Building Sustainability Indicators and Carbon Footprint Analysis (Sadri, 2025).

4 CONCLUSIONS

4.1 Conclusions

This research demonstrates the feasibility of integrating Blockchain Technology (BCT), Digital Twins (DTs), Building Information Modeling (BIM), Internet of Things (IoT), Artificial Intelligence (AI), Machine Learning (ML), and Asset Information Models (AIMs) into an integrated framework for smart Asset Lifecycle Management (ALM) in building facilities. The study responds to persistent challenges in the facility management and real estate sectors, including fragmented information, heterogeneous data sources, limited interoperability, insufficient data traceability, and the difficulty of maintaining reliable information throughout the asset life cycle. The proposed Blockchain-based Digital Twin platform addresses these challenges by establishing a secure and information-rich digital environment in which asset information can be collected, integrated, analyzed, visualized, and exchanged among stakeholders.

The research established a set of functional requirements and Key Performance Indicators (KPIs) covering Asset Information Management, operational efficiency, predictive maintenance and condition monitoring, sustainability, DT integration, and collaboration and information sharing. These requirements provide a structured basis for evaluating smart ALM and demonstrate that effective asset management depends not only on technological integration but also on data quality, accessibility, synchronization, and governance.

The findings further demonstrate the importance of ontology-based AIMs for predictive maintenance. The expert interviews identified the need for well-defined semantic relationships among assets, sensors, environmental conditions, maintenance activities, and operational data. Such relationships can improve semantic interoperability, reduce data silos, support automated reasoning, and provide a foundation for data-driven maintenance decision-making. The study also identified essential ontology classes, including asset definitions, service life expectancy, maintenance activities, maintenance intervals, maintenance costs, personnel, sensor observations, measurement units, and data acquisition frequency.
The Blockchain component contributes an additional layer of trust, traceability, transparency, immutability, and accountability to the Digital Twin environment. The proposed data provenance process establishes a structured sequence of data collection, tagging, validation, processing, storage, and subsequent use for predictive purposes. The integration of on-chain and off-chain data management provides a practical mechanism for handling both immutable transactional records and large operational datasets. Nevertheless, the findings indicate that blockchain implementation remains constrained by implementation costs, large data volumes, heterogeneous information sources, incomplete synchronization infrastructure, and limited cooperation among competing IT suppliers.

The developed use cases demonstrate the practical potential of smart contracts for automating asset management workflows. In the indoor-environment case, sensor data relating to occupancy, temperature, CO_2, and humidity were used to support environmental assessment, predictive analysis, and proactive maintenance. The broader platform extends

this principle by enabling smart contracts to trigger maintenance workflows, payments, information exchange, and other predefined actions when specified conditions are satisfied. This reduces manual intervention, improves workflow efficiency, and supports more transparent and reliable O&M processes.

Overall, the research confirms that a Blockchain-enabled Digital Twin can provide a viable technological foundation for smart ALM. Its principal contribution is not the isolated application of individual technologies, but their integration into a coherent ecosystem that connects physical assets, digital representations, IoT data, semantic information, predictive analytics, blockchain records, and automated decision-support mechanisms. The study therefore provides a foundation for moving FM from reactive and fragmented O&M practices toward proactive, data-driven, secure, and intelligent asset management.

4.2 Recommendations for Future Research

Future studies should first focus on large-scale validation of the proposed Blockchain-based Digital Twin platform across multiple buildings, asset types, organizations, and operational contexts. The present use cases demonstrate feasibility, but broader longitudinal studies are required to quantify improvements in maintenance prediction accuracy, downtime reduction, energy efficiency, maintenance costs, data quality, and stakeholder productivity. Comparative studies involving conventional FM practices and alternative digital platforms would provide stronger evidence of the value generated by blockchain-enabled DTs.

Second, future research should investigate the scalability and performance of blockchain architectures for building-scale and portfolio-scale ALM. Large volumes of IoT and sensor data should not necessarily be stored directly on-chain. Hybrid architectures combining blockchain, cloud or edge computing, distributed databases, and secure off-chain storage should therefore be evaluated in terms of latency, transaction throughput, storage requirements, cybersecurity, and cost. The synchronization between on-chain and off-chain information also requires systematic investigation.

Third, greater attention should be given to the development of standardized ontology-based AIMs for predictive maintenance. Future studies should extend the ontology through alignment with established standards and semantic frameworks such as BIM, BrickSchema, RealEstateCore, IFC, and SAREF. Automated ontology generation using Natural Language Processing (NLP), Named Entity Recognition (NER), Relation Extraction (RE), and Large Language Models (LLMs) should also be investigated to reduce the manual effort required for ontology development and maintenance.

Fourth, future research should strengthen the AI and ML predictive maintenance component by using larger and more diverse datasets and by comparing alternative algorithms. Explainable AI should be incorporated so that facility managers can understand the reasoning behind predicted failures and recommended interventions. Digital Twin simulations should also be validated against physical asset conditions to assess prediction accuracy and model drift over extended operational periods.

Fifth, future studies should examine interoperability, cybersecurity, privacy, and governance in greater depth. Common information exchange protocols and standardized APIs are required to connect BIM, AIM, DT, IoT, BOMS, blockchain, and enterprise systems.

Particular attention should be given to identity management, access control, smart contract vulnerabilities, privacy-preserving mechanisms, and compliance with relevant information-management and data-protection requirements.

Finally, future research should evaluate the platform from the perspective of real users and organizational adoption. Facility managers, asset owners, service providers, tenants, municipalities, and IT suppliers should participate in structured usability evaluations and long-term pilot deployments. Business models, lifecycle costs, organizational readiness, and stakeholder incentives should also be assessed. Such research would help transform the current proof-of-concept into a scalable and commercially viable solution for smart, sustainable, and trustworthy Asset Lifecycle Management.

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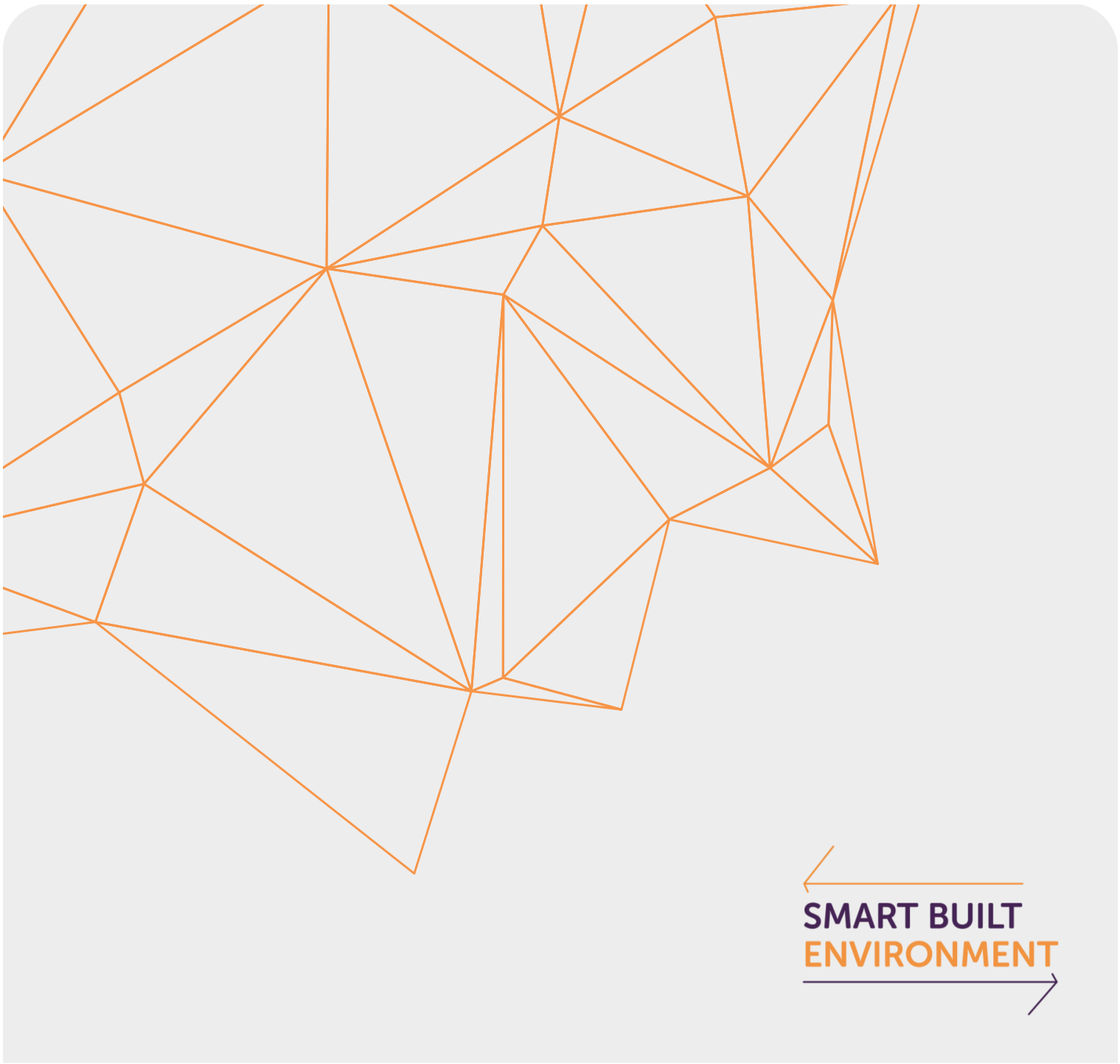

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