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A Data Requirement Framework for BIM–IoT Integration in Sustainable Building Rainwater Drainage Systems

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ABSTRACT

Increasing rainfall intensity and climate variability have heightened the vulnerability of building-scale rainwater drainage systems in dense urban environments. Although Building Information Modeling (BIM) supports the structured representation of physical system characteristics, it primarily manages static data and cannot natively represent dynamic operational behaviour. Internet of Things (IoT) technologies generate time-series monitoring data but are typically implemented independently from BIM, resulting in fragmented information environments. This study proposes a Data Requirement Framework (DRF) to support Building Information Modeling-Internet of Things (BIM–IoT) integration for sustainable planning and management of building rainwater drainage systems. The framework identifies static BIM data and dynamic IoT data requirements, followed by a data gap analysis that categorises missing information into five domains: water level variation, flow performance, rainfall influence, abnormal system conditions, and temporal data referencing. Based on these gaps, five customised Industry Foundation Classes (IFC)-aligned Property Sets (P-Sets) were developed using timestamp-indexed data association: PSet_WaterLevelDynamic, PSet_FlowRateDynamic, PSet_RainfallSensor, PSet_DrainOverflow, and PSet_TimeSeriesReference. The DRF adopts four layers: BIM Static, IoT Dynamic, Integration, and Application. Conceptual validation is conducted using internal consistency and data completeness assessment. The results indicate that the DRF provides a structured data foundation for monitoring, risk assessment, and future digital twin development.

1. INTRODUCTION

Rapid urbanisation combined with climate change has significantly increased the frequency and intensity of extreme rainfall events, placing growing pressure on building-scale rainwater drainage systems [1-3]. In dense urban environments, insufficient drainage capacity and delayed system response can lead to surface flooding, structural damage, service disruption, and long-term degradation of building performance [4, 5]. As a result, effective planning and management of building rainwater drainage systems have become critical components of sustainable urban development.

Building Information Modeling (BIM) has been widely adopted as a digital platform for building design, construction, and lifecycle management [6-10]. By enabling systematic representation of geometric, material, and topological characteristics of building components, BIM provides a comprehensive digital baseline for infrastructure planning and coordination [10]. However, conventional BIM implementations primarily support static information, which limits their ability to represent time-dependent operational behaviour, particularly for systems such as rainwater drainage that are highly sensitive to rainfall variability and usage conditions [3, 5].

In parallel, Internet of Things (IoT) technologies have emerged as a powerful tool for real-time monitoring of building and infrastructure systems [2, 11]. Sensor-based monitoring of variables such as water level, flow rate, rainfall intensity, and system status provides valuable time-series data that reflect actual system performance under varying environmental conditions [11, 12]. Despite this potential, IoT-based monitoring systems are often implemented independently from BIM models, resulting in fragmented data environments that constrain integrated planning, risk assessment, and decision support [12, 13].

Recent research has increasingly explored Building Information Modeling-Internet of Things (BIM–IoT) integration within the contexts of smart buildings and digital twins, demonstrating the technical feasibility of linking sensor data with digital building models [14]. These studies highlight potential benefits for system monitoring, optimisation, and lifecycle management. Nevertheless, much of the existing literature focuses on system implementation or application-specific solutions, while comparatively limited attention has been given to the underlying structure of data integration. In particular, there remains a lack of clarity regarding the definition of required data, the association of dynamic IoT data with BIM elements, and the systematic resolution of inconsistencies between static and dynamic data domains [15].

These challenges are especially pronounced for building rainwater drainage systems, where system performance is governed by both fixed physical characteristics, such as pipe geometry and network configuration, and highly dynamic operational conditions driven by rainfall events [3]. Without a structured definition of data requirements, BIM–IoT integration risks becoming ad hoc, thereby limiting its contribution to sustainable drainage planning, system resilience, and long-term decision-making.

To address these limitations, this study proposes a Data Requirement Framework (DRF) for integrating BIM and IoT data to support sustainable planning and management of building rainwater drainage systems. The proposed framework explicitly distinguishes between static BIM data and dynamic IoT data, identifies data gaps between these two information domains, and introduces a structured integration mechanism based on customised Property Sets (P-Sets) and a layered data architecture. Rather than focusing on sensor deployment or software implementation, the DRF provides a data-centric and planning-oriented foundation for consistent BIM–IoT integration, enabling improved monitoring, risk assessment, and future digital twin development.

The research workflow is organised into five sequential stages: (1) identification of BIM static data, (2) definition of IoT dynamic data requirements, (3) data gap analysis between static and dynamic information domains, (4) development of customised P-Sets, and (5) design of the DRF architecture for BIM–IoT integration.

This study makes three primary contributions. First, it systematically categorises BIM–IoT data gaps in building rainwater drainage systems into five structural domains, providing explicit data gap classification rather than general integration discussion. Second, it develops a structured set of IFC-aligned customised P-Sets that formally define data type, temporal format, and BIM element association for time-series integration. Third, it proposes a layered DRF that operationalises data interoperability without modifying the core BIM schema, thereby enhancing architectural readiness for digital twin development in building-scale drainage management.

The remainder of this paper is organised as follows. Section 2 reviews relevant literature on BIM, IoT, data integration challenges, and digital twin concepts related to building drainage systems. Section 3 presents the research methodology and the proposed DRF. Section 4 discusses the results of data identification, data gap analysis, framework development, data flow modeling, and conceptual validation. Section 5 concludes the study by summarising the main findings and limitations, while Section 6 outlines directions for future work.

2. LITERATURE REVIEW

2.1 Building Information Modeling for building system management

BIM has been widely recognized as a core digital platform for supporting building design, construction, and lifecycle management [10, 16-22]. By integrating geometric, material, and relational information within a unified digital environment, BIM enables systematic representation of building components and infrastructure systems, thereby improving coordination, reducing design conflicts, and supporting long-term asset management [8, 11].

Despite these advantages, numerous studies have highlighted that conventional BIM implementations are primarily designed to manage static information [16, 18]. Such data structures are well-suited to representing physical characteristics and design intent, but are limited in their ability to capture dynamic operational behaviour during the building use phase [18, 19]. This limitation is particularly significant for systems whose performance varies over time, such as rainwater drainage systems, which are highly sensitive to rainfall variability and transient flow conditions [3].

In the context of building rainwater drainage, BIM is commonly used to model pipe geometry, network topology, and material properties [10]. While this information provides an essential structural baseline, it does not offer insight into real-time system performance or operational risks [16]. As a result, BIM alone is insufficient to support performance monitoring, adaptive management, or sustainability-oriented planning of drainage systems [19].

2.2 Internet of Things and dynamic data for drainage systems

The rapid development of IoT technologies has enabled real-time monitoring of infrastructure and building systems through distributed sensor networks [2, 11]. IoT devices generate continuous time-series data related to water level, flow rate, pressure variation, rainfall intensity, and system status, thereby providing valuable information on actual system behaviour under varying operational conditions [19].

In water and drainage management, IoT-based monitoring has been applied to urban drainage networks, flood warning systems, and smart water infrastructure [12, 19]. These applications demonstrate the potential of dynamic data to enhance system responsiveness and risk mitigation. However, much of the existing research emphasises sensor technology, data acquisition, and communication protocols, with comparatively limited attention given to how dynamic data should be structurally integrated with existing building information models [17].

Within building-scale rainwater drainage systems, IoT data are often collected and stored independently from BIM models [15]. This separation results in fragmented data environments in which real-time monitoring data cannot be directly linked to the physical components represented in BIM. Consequently, the analytical and decision-support potential of IoT data remains underutilised in sustainable building system management [6].

2.3 Data gap between Building Information Modeling and Internet of Things integration

Although BIM and IoT each provide significant benefits when considered independently, their integration presents substantial challenges due to fundamental differences in data characteristics [6, 16]. BIM primarily manages structured, object-based, and static data, whereas IoT systems generate unstructured or semi-structured, time-dependent data streams [2, 11]. This mismatch creates a data gap that hinders seamless integration and limits the effectiveness of combined BIM–IoT systems.

Previous studies have identified the lack of semantic mapping and data alignment mechanisms as a major obstacle to BIM–IoT integration [16, 17]. Without clear definitions of data requirements and relationships, dynamic sensor data cannot be consistently associated with BIM elements, reducing the reliability of system assessment and analysis [6]. This issue is particularly critical for rainwater drainage systems, where operational behaviour is governed by rapid temporal variations in rainfall and flow conditions [3, 19].

Moreover, the absence of a structured data integration framework increases the risk of ad hoc solutions that are difficult to scale, maintain, or generalise across projects [18, 22]. These limitations highlight the need for a systematic approach to defining and managing data requirements for BIM–IoT integration.

2.4 Property Sets and limitations of Industry Foundation Classes-based data structures

The Industry Foundation Classes (IFC) standard has been developed to support interoperability in BIM by providing a common data schema for building information exchange [7, 10]. Within IFC, P-Sets enable flexible attachment of attribute information to BIM elements, supporting extensible representation of component properties [7].

However, existing standard P-Sets primarily focus on physical and static attributes, such as dimensions, materials, and classification codes [10, 22]. They provide limited support for representing dynamic, time-series data required to describe operational system behaviour, including water level fluctuations, flow variability, and abnormal system states [16, 18]. As a result, standard IFC-based data structures are insufficient to support BIM–IoT integration for drainage systems without structural extension [6].

Several studies have explored the use of customised P-Sets to accommodate sensor data and digital twin applications [16, 17]. While these approaches demonstrate technical feasibility, they often lack a systematic framework for defining data requirements, identifying data gaps, and structuring extensions in a manner that supports sustainable planning and long-term system resilience [6].

2.5 Digital twin concepts and the need for conceptual data frameworks

Digital twin concepts have gained increasing attention as a means of linking digital models with real-time operational data to support system monitoring, analysis, and decision-making [6, 13]. In the context of buildings and infrastructure, digital twins are expected to enhance predictive capabilities and improve system resilience under changing environmental conditions [17, 18]. Similar concepts have also been discussed in sponge city initiatives aimed at improving urban stormwater resilience and adaptive water management under climate variability [20].

Recent studies emphasise that successful digital twin development depends not only on sensor deployment or software platforms but also on the availability of well-defined data structures and integration frameworks at the conceptual level [6, 12]. Without clear data requirements and integration logic, digital twin implementations risk becoming fragmented, project-specific, and difficult to sustain [21].

For building rainwater drainage systems, the absence of a dedicated conceptual data framework limits the ability to translate BIM–IoT integration into practical decision-support tools for sustainable planning and risk management [16, 17].

2.6 Research gap and study positioning

Based on the reviewed literature, three key research gaps can be identified. First, there is a lack of dedicated DRF specifically designed for integrating BIM and IoT in building rainwater drainage systems [6, 17]. Second, existing BIM standards and data structures do not adequately support the representation of dynamic, time-dependent operational data required for drainage system monitoring and assessment [16, 18]. Third, the development of digital twins for drainage systems lacks a robust conceptual data foundation to support sustainable planning and long-term resilience [13, 21].

To address these gaps, this study proposes a DRF that systematically defines static and dynamic data types, identifies data gaps, and establishes structured integration mechanisms between BIM and IoT. By focusing on data requirements and architectural design rather than system implementation, the proposed framework provides a scalable and sustainability-oriented foundation for future digital twin development and decision-support applications in building rainwater drainage management.

2.7 Comparative positioning of Building Information Modeling-Internet of Things integration frameworks

To position the proposed DRF within the broader context of BIM–IoT integration research, a structured comparison of representative prior frameworks is presented in Table 1. The comparison focuses on drainage specificity, time-series integration capability, IFC extension strategy, and architectural layering. This analysis clarifies the distinctive scope and technical positioning of the proposed DRF.

Table 1. Comparative analysis of Building Information Modeling-Internet of Things (BIM–IoT) integration frameworks

Study	Drainage-Specific Focus	Time-Series Linking	IFC Extension Strategy	Layered Architecture
Ali et al. [14]	No (general building systems)	Partial (sensor mapping)	Limited	No explicit layering
Boje et al. [4]	No	Yes (digital twin data flow)	Conceptual	Middleware-oriented
Zhang et al. [21]	No	Yes	No explicit IFC extension	Platform-based
Tagliabue et al. [23]	Partial (urban drainage)	Limited	No	Not layered
This study (DRF)	Yes (building rainwater drainage)	Explicit timestamp-indexed integration	IFC-aligned customised P-Sets	Four-layer DRF architecture

Notes: IFC: Industry Foundation Classes, DRF: Data Requirement Framework, P-Sets: Property Sets.

As shown in Table 1, existing BIM–IoT integration studies generally focus on middleware connectivity, digital twin platforms, or general building monitoring applications. However, few frameworks explicitly address drainage-specific data requirements, structured time-series linkage at the schema level, and IFC-aligned extension mechanisms within a layered architectural model. The proposed DRF distinguishes itself by systematically categorising drainage-related data gaps and formalising their integration through customised P-Sets within a four-layer architecture.

3. RESEARCH METHODOLOGY

3.1 Research design and overall methodology

This study adopts a conceptual and framework-based research design with the objective of developing a DRF for integrating BIM and IoT data to support sustainable management of building rainwater drainage systems [6, 17]. The research focuses on defining data requirements, identifying structural information gaps between static and dynamic data domains, and designing a systematic data integration architecture. The scope of the study emphasises data modeling and information architecture rather than physical sensor installation or field experimentation [16].

The research methodology is organised as a sequential and interconnected workflow that links each stage of framework development. The process begins with a case study building analysis to establish system context and identify relevant drainage components. Based on this analysis, BIM static data (B) are identified to represent the physical and topological characteristics of the drainage network, while IoT dynamic data requirements (I) are defined to capture expected operational behaviour [9, 19].

Subsequently, a data gap analysis (G = I-B) is conducted to identify information that cannot be represented using conventional BIM data structures. The identified data gaps form the basis for developing customised P-Sets, which extend BIM attributes to accommodate time-series data [6, 16]. These P-Sets are then incorporated into the design of the DRF architecture, providing a structured mechanism for integrating BIM and IoT data.

Following framework development, data flow and risk modeling are conceptually applied to demonstrate how integrated data can support system assessment and decision-making [19]. The methodology concludes with conceptual validation, which focuses on internal consistency, data completeness, and the feasibility of information integration. This structured approach ensures that the proposed DRF is grounded in realistic system characteristics while remaining adaptable for sustainable planning and future digital twin development [13]. The overall research methodology adopted in this study is illustrated in Figure 1.

The proposed DRF was developed and examined using a real-world case study building to ensure contextual grounding under realistic drainage system conditions. The selected case is the Engineering and Electric Vehicle Innovation Building (EN4) located at Mahasarakham University, Thailand. The building is a two-storey academic and research facility comprising interconnected functional spaces and a gravity-based internal rainwater drainage network.

Based on construction drawings, BIM model examination, and field verification during project supervision, the building-scale stormwater drainage network includes reinforced concrete pipes with diameters of 0.40 m and 0.60 m and an approximate documented pipe network length of 110 m. The roof drainage system consists of stainless-steel gutters connected to two primary vertical rainwater downpipes that convey runoff to underground stormwater pipes and inspection chambers before discharge to the external drainage system.

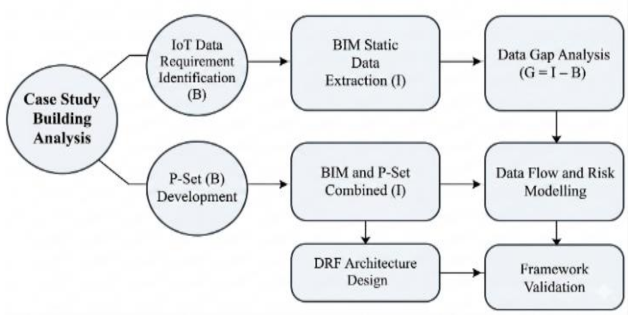

Figure 1. Workflow for developing the Data Requirement Framework (DRF), including Building Information Modeling (BIM) data extraction (B), Internet of Things (IoT) requirements identification (I), and data gap analysis (G = I-B), followed by Property Sets (P-Set) development, architecture design, risk modeling, and validation

Architectural and construction drawings were used to verify system configuration, pipe routing, flow direction, discharge locations, and roof drainage connections. The BIM model was developed and analysed using Autodesk Revit at approximately Level of Development (LOD) 300, enabling the extraction of geometric, topological, and material attributes of drainage components for structured static data identification.

The case study focuses exclusively on building-scale rainwater drainage infrastructure, including roof runoff collection, internal piping, and discharge from the building perimeter. Combined sewer systems and municipal drainage networks are outside the scope of this study. This defined system boundary ensures that the proposed DRF is grounded in realistic building conditions while maintaining a clearly controlled analytical scope.

3.2 Proposed Data Requirement Framework

This study proposes a DRF for integrating BIM and time-series data derived from IoT-based monitoring systems to support systematic management of building rainwater drainage systems. The DRF is designed to address limitations of conventional BIM in representing dynamic operational behaviour and to reduce structural data gaps between design information and actual system performance [6, 16].

The proposed DRF is structured as a four-layer architecture, comprising:

(1) BIM Static Layer
(2) IoT Dynamic Layer
(3) Integration Layer
(4) Application Layer

The BIM Static Layer stores geometric and static attribute data of the rainwater drainage system, such as pipe dimensions, slopes, connectivity, and material properties [9]. These data represent the physical configuration of the system and provide a reference baseline for data integration. However, this layer alone cannot describe system behaviour under varying operational conditions [14].

The IoT Dynamic Layer represents time-series data requirements that reflect actual system performance, including water level, flow rate, rainfall intensity, and system status [1, 16]. These data capture temporal variations essential for monitoring and risk assessment, but cannot be directly accommodated within standard BIM data structures [11].

The Integration Layer serves as the core component of the DRF, enabling systematic linkage between BIM static data and IoT dynamic data. This layer employs data gap analysis (G = I-B), data mapping mechanisms, and customised P-Sets to bridge inconsistencies between heterogeneous data domains. Through this process, time-series data are meaningfully associated with corresponding BIM elements.

Finally, the Application Layer represents a conceptual layer for utilising integrated data in system analysis, monitoring, and decision support [12].

This layer also provides a foundation for future digital twin development by enabling continuous linkage between physical drainage systems and their digital representations [7]. The identification of variables presented in Table 2 and Table 3 was conducted through a structured selection strategy grounded in (i) literature synthesis on BIM–IoT integration and drainage monitoring, (ii) examination of construction drawings and the LOD 300 Revit-based BIM model of the case study building, and (iii) functional analysis of rainwater drainage behaviour under varying rainfall conditions. Static variables were restricted to attributes extractable from the BIM environment that influence hydraulic configuration and connectivity, while dynamic variables were defined based on measurable operational states and risk scenarios. This structured approach ensures traceability between data definition (Sections 3.3 and 3.4), data presentation (Section 4), and P-Set development (Section 3.6) within the DRF.

3.3 Identification of Building Information Modeling static data (B)

In this stage, the study identifies and classifies static data that can be extracted from BIM models to represent the structural characteristics of the building's rainwater drainage system [9, 14]. These data serve as the physical baseline for subsequent integration with time-series data and are inherently time-invariant.

The identified BIM static data (B) are classified into three main categories:

(1) geometric properties
(2) topological properties
(3) material properties

Geometric data include pipe diameter, length, slope, and elevation, while topological data describe connectivity relationships, flow direction, and network configuration [9]. Material properties provide supporting information related to durability and service life [14]. Although these data adequately describe the system structure, they are insufficient to represent operational behaviour under varying rainfall conditions, highlighting the need for dynamic data integration [11].

3.4 Identification of Internet of Things dynamic data requirements (I)

To support effective monitoring and assessment of rainwater drainage system performance, this study defines a set of dynamic data requirements derived from IoT-based monitoring [1, 6]. These requirements are identified based on typical flow behaviour and potential operational risks, such as overflow, insufficient drainage capacity, and blockage [3, 16].

The identified IoT dynamic data (I) include time-series variables such as water level, flow rate, pressure variation, rainfall intensity, and system status indicators [16]. Although no physical sensor deployment is undertaken in this study, defining these data requirements is essential for determining how BIM data structures should be extended to support future integration of operational data and digital twin applications [4, 11].

3.5 Data gap analysis (G = I-B)

By comparing the identified BIM static data (B) with the defined IoT dynamic data requirements (I), this study conducts a data gap analysis to identify information that is essential for monitoring and managing building rainwater drainage systems but cannot be accommodated within conventional BIM data structures [4, 11]. The data gap represents missing or unsupported information that prevents BIM models from reflecting actual system behaviour under operational conditions [14, 15].

The data gap is conceptually defined using the following relationship:

$$G = \{x \mid x \in I \text{ and } x \notin B\} \tag{1}$$

where, G represents the data gap, x denotes an individual data element considered in the comparison process, I denotes the required dynamic, time-series data derived from IoT-based monitoring, and B represents static data extracted from BIM models.

The analysis reveals that, although BIM can comprehensively represent the geometric configuration, material properties, and topological structure of the rainwater drainage system, it cannot natively support time-dependent variables such as water level variation, flow rate fluctuation, rainfall forcing, or abnormal system status [11, 14]. These limitations result in a structural data gap that restricts the application of BIM for system monitoring, risk assessment, and digital twin development [4, 15].

To clearly illustrate the nature of this data gap and its role in the proposed research methodology, Figure 2 presents a conceptual representation of the relationship between BIM static data (B), IoT dynamic data requirements (I), and the resulting data gap (G). As shown in the figure, the data gap emerges from the inability of static BIM data to represent required dynamic system behaviour, thereby forming the basis for subsequent data integration and framework development.

This conceptual representation provides a logical bridge between data identification (Sections 3.3 and 3.4) and the development of data integration mechanisms under the DRF. By explicitly visualizing the data gap, Figure 2 clarifies why structural extensions-such as customised P-Sets-are required to enable systematic BIM–IoT integration.

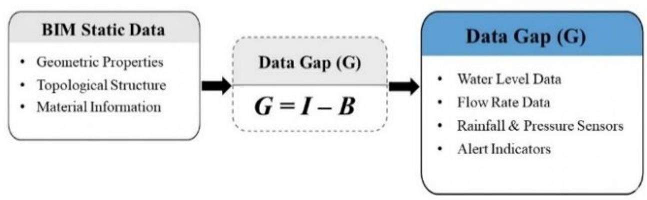

Figure 2. Conceptual framework of the data gap between Building Information Modeling (BIM) static data and Internet of Things (IoT) dynamic data requirements

The results of this data gap analysis serve as a foundational input for the development of the DRF architecture presented in Section 3.6 and are further examined at the system and component levels in the Results and Discussion section.

Figure 2 illustrates the conceptual relationship between static data derived from BIM and the required time-series data obtained from IoT–based monitoring for building rainwater drainage systems. The data gap, defined as G = I-B, represents information that cannot be accommodated within conventional BIM data structures and forms the conceptual basis for the development of the proposed DRF.

3.6 Development of the Data Requirement Framework

Based on the identification of BIM static data (B) and the definition of IoT dynamic data requirements (I) presented in the preceding sections, the data gap analysis highlights a fundamental limitation of conventional BIM data structures in representing the actual operational behaviour of building rainwater drainage systems [11, 14]. While BIM provides a comprehensive description of physical configuration and connectivity, it cannot adequately accommodate time-dependent information required for monitoring system performance under varying rainfall conditions [15].

To address this limitation, this study develops a DRF as a data-centric architectural framework for systematic integration of BIM and IoT data. The DRF is designed to function as an intermediary structure that links static design information with dynamic operational data while preserving the integrity of the original BIM model. Rather than modifying the core BIM schema, the framework introduces structured data extensions that enable consistent association of time-series data with BIM elements [4].

The proposed DRF adopts a four-layer architecture comprising the BIM Static Layer, IoT Dynamic Layer, Integration Layer, and Application Layer. Each layer has a distinct role in managing data characteristics and supporting interoperability between static and dynamic data domains. In particular, the Integration Layer serves as the central mechanism for resolving data gaps identified in Section 3.5 by enabling systematic data mapping and alignment between BIM and IoT data [14].

To clearly illustrate the architectural organisation and functional interaction among these layers, Figure 3 presents the four-layer structure of the proposed DRF.

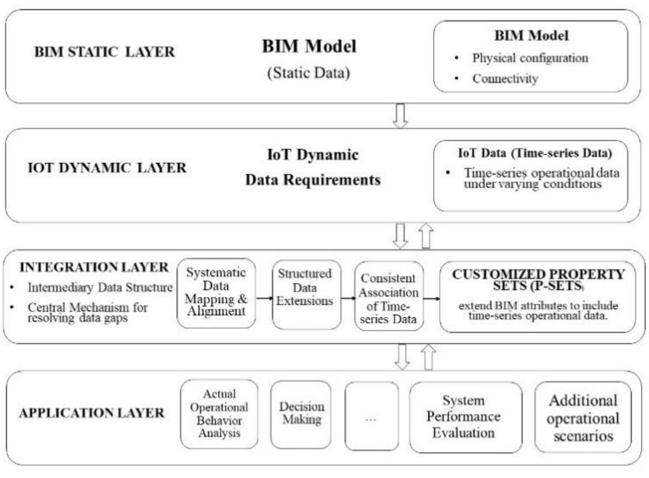

Figure 3. Four-layer architecture of the proposed Data Requirement Framework (DRF)

Figure 3 illustrates the conceptual architecture of the DRF, highlighting the interaction between the BIM Static Layer, IoT Dynamic Layer, Integration Layer, and Application Layer. The Integration Layer acts as the intermediary mechanism that systematically maps static BIM attributes to dynamic time-series data through structured extensions, enabling consistent linkage without altering the core BIM schema.

A key component of the DRF is the use of customised P-Sets to extend BIM attributes so that dynamic, time-series data can be associated with corresponding BIM elements, such as pipes, chambers, and drainage terminals [2, 9]. This approach is consistent with IFC-based extension mechanisms and ensures that dynamic data integration can be achieved without altering the core BIM data structure.

Time-series attributes are structured as timestamp-indexed records compliant with ISO 8601 temporal standards and are linked to IFC-based BIM elements through unique element identifiers (e.g., IfcPipeSegment, IfcChamber). This structured definition ensures interoperability, traceability, and schema-level consistency within the Integration Layer without modifying the core BIM schema.

The conceptual relationship underpinning the DRF can be expressed as:

$$P = f(B,\ I) \tag{2}$$

where, P represents BIM-linked properties generated through the integration process, B denotes static data extracted from BIM models, I represents dynamic data requirements derived from IoT-based monitoring, and $f(\cdot)$ denotes the data mapping and integration logic implemented within the Integration Layer through the use of customised P-Sets. This expression is intended to describe a conceptual integration mechanism, rather than a quantitative computational model.

To ensure technical clarity, each developed P-Set follows a structured definition including attribute name, data type, unit specification, temporal reference format, SensorID, and BIM element association. Time-series attributes are defined using timestamp-indexed data structures and are linked to specific IFC-based BIM elements through unique element identifiers and sensor reference fields. This structured specification ensures traceability, schema interoperability, and consistency of data mapping within the Integration Layer.

By structuring data integration in this manner, the proposed DRF provides a systematic foundation for linking design information with operational data, thereby enabling subsequent application-level use cases such as system monitoring, risk assessment, and preparation for future digital twin development. The DRF architecture developed in this section forms the methodological basis for the results and discussion presented in Section 4.

3.7 Conceptual validation approach

The validation of the proposed DRF is conducted using a conceptual validation approach, as the scope of this study focuses on data structure definition and architectural design rather than physical sensor deployment or empirical system testing. This validation strategy is consistent with framework-based research and architectural information system studies, where validation emphasises conceptual soundness, internal consistency, and feasibility of integration rather than quantitative performance evaluation.

The conceptual validation focuses on three key aspects: (i) structural consistency of data across the DRF layers, (ii) completeness of required variables to support monitoring and analysis of building rainwater drainage systems, and (iii) feasibility of data flow and linkage between BIM static data and IoT dynamic data through the Integration Layer. These aspects collectively ensure that the proposed framework can logically support systematic BIM–IoT integration under the defined architectural structure.

To describe the conceptual validation logic of the DRF, the validity condition of the framework can be expressed using the following relationship:

$$V = g(B,\ I,\ P, A) \tag{3}$$

where, V represents the conceptual validity of the DRF; B denotes static data derived from BIM; I represents dynamic, time-series data requirements derived from IoT-based monitoring; P denotes the P-Sets used as the primary integration mechanism; A represents application-level utilisation of integrated data; and $g(\cdot)$ denotes the evaluation logic used to assess structural consistency, data completeness, and integration feasibility within the DRF architecture. This expression is intended to describe a conceptual validation framework rather than to perform quantitative computation.

Although no physical sensor installation or field-based system testing is conducted in this study, the conceptual validation confirms that the proposed DRF is structurally sound and architecturally ready for extension toward future implementation. In particular, the validation demonstrates that the DRF can support systematic linkage between static BIM data and dynamic IoT data, manage identified data gaps through structured extensions, and prepare integrated datasets for application-level use.

Overall, this conceptual validation approach confirms the suitability of the proposed DRF as a foundational framework for BIM–IoT data integration in building rainwater drainage systems. It provides a necessary preparatory step toward future empirical studies, digital twin development, and sustainability-oriented planning applications, which are further explored in the Results and Discussion section.

4. RESULTS AND DISCUSSION

Following the methodological framework presented in Section 3, this section reports the results derived from the identification of BIM static data, the definition of IoT dynamic data requirements, the data gap analysis, and the development of data integration mechanisms under the proposed DRF. The results are discussed to demonstrate how the proposed framework addresses structural limitations of conventional BIM and supports sustainability-oriented planning and management of building rainwater drainage systems.

4.1 Identification of Building Information Modeling static data

Based on the methodology described in Section 3.3, BIM static data representing the physical configuration of the building's rainwater drainage system were systematically extracted from the BIM model of the case study building. These data constitute the structural baseline of the system and correspond directly to the static data domain (B) within the proposed DRF.

To support structured utilisation and subsequent integration with dynamic data, the extracted BIM static data were classified into three main categories: geometric properties, structural/topological properties, and material properties, as summarised in Table 2. Geometric properties include pipe diameter, length, slope, and elevation, which define the physical capacity and spatial characteristics of the drainage system. Structural and topological properties describe connectivity relationships, flow direction, and network hierarchy, enabling consistent mapping of operational data to specific BIM elements. Material properties provide supporting information related to durability and maintenance considerations.

The variables listed in Table 2 were derived using the structured selection strategy defined in Section 3.2.

Table 2. Categories of Building Information Modeling (BIM) static data for building rainwater drainage systems

No.	Data Category	Example Variables	Role within the DRF
1	Geometric properties	Pipe diameter, pipe length, slope, elevation	Provide a structural basis for defining system capacity and serve as reference attributes for linking time-series data (e.g., identifying the physical location associated with sensor data).
2	Structural / topological properties	Junctions, connectivity relationships, flow direction, pipe network topology	Function as a network map for correctly mapping time-series data to BIM elements and for identifying structurally vulnerable locations (e.g., junctions or direction changes).
3	Material properties	Pipe material type (e.g., PVC, HDPE), material specifications	Support interpretation of durability and risk, and act as metadata for engineering analysis and future maintenance planning.

Notes: DRF: Data Requirement Framework

Table 2 summarises the categories of static data extracted from the BIM model, which constitute the structural baseline (B) of the building rainwater drainage system within the proposed DRF. Geometric and topological properties provide reference attributes for linking time-series operational data to physical BIM elements, while material properties support interpretation related to durability and long-term planning.

The results demonstrate that BIM static data can comprehensively represent the physical layout and connectivity of the rainwater drainage network. However, these data are inherently time-invariant and do not reflect variations in system behaviour during rainfall events or operational disturbances. As a result, BIM static data alone are insufficient to support performance monitoring or risk assessment, underscoring the necessity of integrating dynamic, time-series data within the DRF.

4.2 Internet of Things dynamic data requirements

Following the limitations identified in Section 4.1, where BIM static data were shown to be insufficient for representing time-dependent system behaviour, this section presents the results of defining dynamic data requirements derived from IoT-based monitoring. These dynamic data represent the operational domain (I) within the proposed DRF and are essential for capturing the actual performance of building rainwater drainage systems under varying rainfall conditions.

Based on the functional characteristics of rainwater drainage systems and potential operational risks, a set of key dynamic variables was identified. These variables include water level, flow rate, pipe pressure, rainfall intensity, and system status indicators such as overflow or blockage conditions. All identified variables are characterised as time-series data that reflect temporal variations in system behaviour and external forcing, as summarised in Table 3.

The dynamic variables summarised in Table 3 follow the selection logic described in Section 3.2.

Table 3. Internet of Things (IoT) dynamic data requirements for building rainwater drainage systems

No.	Data Type	Data Variables	Role in Analysis and DRF
1	Water level	Measured water level at a given time	Reflects internal flow conditions and serves as an indicator of overflow risk or insufficient drainage capacity.
2	Flow rate	Instantaneous flow rate, average flow, peak flow	Used to assess drainage performance and system capacity under different rainfall scenarios.
3	Pipe pressure	Pressure at monitoring locations	Enables detection of abnormal conditions such as blockage or unexpected flow behaviour.
4	Rainfall intensity	Rainfall amount, intensity, and duration	Represents external forcing conditions linked to the drainage system response.
5	System status	Overflow signals, warning or alarm states	Supports real-time alerting and decision-making for system management.

Notes: DRF: Data Requirement Framework

Table 3 summarises the key time-series data required to represent the operational behaviour of building rainwater drainage systems. These dynamic variables constitute the IoT data domain (I) within the proposed DRF and provide essential information for monitoring system performance and identifying operational risks that cannot be captured by static BIM data alone.

The identified IoT dynamic data requirements are summarised in Table 3, which presents the required variables, their functional relevance, and their roles in system monitoring and assessment. Although this study does not involve physical sensor installation or real-time data acquisition, defining these data requirements provides a structured foundation for subsequent BIM–IoT integration and prepares the data architecture for future implementation and digital twin development.

The results highlight that dynamic data are indispensable for interpreting system performance during rainfall events and identifying abnormal operating conditions. However, when considered independently, IoT-derived data lack inherent linkage to physical system components represented in BIM models. This limitation reinforces the need for a structured integration mechanism, which is addressed through data gap analysis in Section 4.3.

4.3 Data gap analysis

Building upon the identified BIM static data (Section 4.1) and IoT dynamic data requirements (Section 4.2), a data gap analysis was conducted to examine discrepancies between the two data domains. The analysis aims to identify information required for monitoring and managing building rainwater drainage systems that cannot be represented within conventional BIM data structures.

The data gap was formally defined using the conceptual relationship G = I−B, where *G* represents missing or unsupported information, I denotes required dynamic, time-series data, and B represents static data extracted from BIM models. By systematically comparing these two data domains, critical gaps related to operational system behaviour were identified.

Table 4. Linkage between BIM–IoT data gaps and developed P-Sets

Data Gap Category	Existing BIM Static Data	IoT Dynamic Data Requirements	Identified Data Gap	Developed P-Set	Target BIM Element
Internal pipe flow conditions	Pipe diameter, slope, length, invert level	Real-time water level	BIM cannot represent temporal water level variation	PSet_WaterLevelDynamic	IfcPipeSegment
Drainage performance	Pipe network and connectivity	Flow rate (instantaneous / peak)	Lack of real flow performance data	PSet_FlowRateDynamic	IfcPipeSegment
Rainfall influence	Roof area and inlet layout	Rainfall intensity and duration	No linkage between rainfall data and the pipe system	PSet_RainfallSensor	IfcSite / IfcFlowTerminal
System abnormal conditions	Discharge points and chambers	Overflow status, blockage probability	BIM cannot indicate abnormal events	PSet_DrainOverflow	IfcChamber / IfcFlowTerminal
Temporal data referencing	Static object identifiers	Time-series data	Time-series data cannot be associated with BIM objects	PSet_TimeSeriesReference	All drainage system elements

Notes: BIM–IoT: Building Information Modeling-Internet of Things, BIM: Building Information Modeling, IOT: Internet of Things, P-Sets: Property Sets

The results of the data gap analysis are summarised in Table 4, which links BIM-supported information, required IoT dynamic data, identified data gaps, and corresponding data extension mechanisms. As shown in the table, while BIM static data comprehensively describe the physical configuration and connectivity of the drainage system, they do not support key operational variables such as water level variation, flow performance, rainfall influence, and abnormal system states.

Table 4 presents the results of the data gap analysis by mapping BIM static data against required IoT dynamic data for building rainwater drainage systems. The table highlights operational variables that cannot be represented within conventional BIM data structures and identifies corresponding gaps that necessitate structural data extensions.

The results presented in Table 4 demonstrate that the identified data gaps arise primarily from the inability of BIM to accommodate time-dependent and event-driven information rather than from deficiencies in model completeness or geometric detail. These gaps are therefore structural in nature and cannot be resolved by adding further static attributes to the BIM model.

Consequently, addressing the identified data gaps requires a structured data integration mechanism capable of extending BIM attributes to support dynamic information. This requirement provides the rationale for the development of customised P-Sets, which are presented and discussed in Section 4.4 as a core component of the proposed DRF.

4.4 Development and role of Property Sets

Based on the data gaps identified in Section 4.3, customised P-Sets were developed as a structural mechanism for extending BIM data models to support systematic integration of IoT-derived time-series data. The development of P-Sets focuses on enabling dynamic operational information to be associated with relevant BIM elements without modifying the core BIM schema.

The developed P-Sets address key operational variables that cannot be represented by conventional BIM attributes, including water level variation, flow performance, rainfall influence, and abnormal system states. These dynamic attributes are defined as time-series properties and are linked to specific BIM components such as pipes, inspection chambers, and drainage terminals. Through this approach, P-Sets function as an intermediary data structure that bridges static BIM data and dynamic IoT data within the proposed DRF.

The developed P-Sets and their associated data variables are summarised in Table 5, which presents the relationship between dynamic operational parameters and corresponding BIM elements. The table demonstrates how each identified data gap is addressed through a structured extension of BIM attributes, thereby enabling consistent association of time-series data with physical system components.

Table 5 provides the technical specification of the developed P-Sets, including attribute data types, unit definitions, temporal referencing formats, and sensor linkage attributes. Time-series data are structured using TimestampID and are associated with BIM elements through IFC-based element identifiers and SensorID fields. This specification ensures consistent data interoperability without modification of the core BIM schema.

Table 5. Developed Property Sets (P-Sets) for building rainwater drainage systems

P-Set Name	Data Attribute	Data Type	Unit	Temporal Format	Associated BIM Element
PSet_WaterLevelDynamic	WaterLevel	Float	m	Timestamped (ISO 8601)	IfcPipeSegment
PSet_FlowRateDynamic	Flow Rate	Float	L/s	Timestamped	IfcPipeSegment
PSet_RainfallSensor	RainfallIntensity	Float	mm/h	Timestamped	IfcFlowTerminal
PSet_DrainOverflow	OverflowStatus	Boolean	–	Event-based	IfcChamber
PSet_TimeSeriesReference	TimestampID	String	–	ISO 8601	All drainage elements
PSet_TimeSeriesReference	SensorID	String	–	Static reference	All drainage elements

Notes: All P-Sets are designed to be extensible and updatable without affecting the core BIM data structure. BIM: Building Information Modeling

The results presented in Table 4 indicate that customised P-Sets can effectively resolve the structural data gaps identified in Section 4.3 by enabling dynamic operational data to be coherently linked to BIM elements. This structured linkage allows BIM models to conceptually reflect system behaviour under varying rainfall and operational conditions while preserving their original design-oriented structure.

The role of P-Sets within the overall DRF architecture is conceptually illustrated in Figure 4, which shows how static BIM data and dynamic IoT data are integrated through the Integration Layer, temporal indexing, and BIM element identification to ensure structured transformation of time-series attributes within the DRF. As shown in the figure, P-Sets serve as the primary mechanism for associating time-series data with BIM elements, enabling integrated data flow toward application-level use cases such as monitoring, risk assessment, and preparation for digital twin development.

Figure 4 illustrates the conceptual integration of BIM static data and IoT dynamic data through customised P-Sets under the proposed DRF. The figure highlights the role of the Integration Layer in linking time-series operational data to BIM elements to support monitoring, risk analysis, and future digital twin applications.

By establishing a structured mechanism for BIM–IoT data linkage, the developed P-Sets provide the foundation for systematic data transformation and utilisation within the DRF. Building upon this integration mechanism, the following section presents data flow modeling results to demonstrate how integrated data are transformed into decision-ready information under the proposed framework.

4.5 Data flow modeling under the Data Requirement Framework

Building upon the integration mechanism established through customised P-Sets in Section 4.4, data flow modeling was conducted to demonstrate how integrated BIM–IoT data are transformed into decision-ready information under the proposed DRF. The data flow modeling focuses on logical data movement and transformation across the DRF layers rather than on software-specific implementation. The modeling explicitly incorporates data typing, temporal indexing, and IFC-based element identification to ensure structured transformation of time-series attributes into BIM-linked dynamic properties.

The data flow begins at the IoT Dynamic Layer, where time-series data representing system operation—such as water level, flow rate, and rainfall intensity—are generated. These data are subsequently transferred to the Integration Layer, where validation, consistency checking, and semantic alignment with BIM elements are performed. Through the use of customised P-Sets, validated time-series data are then associated with corresponding BIM components, enabling structured linkage between dynamic operational data and static system representations.

The sequence of data flow processes under the DRF is summarised in Table 6, which outlines the transformation of data from acquisition to application-level utilisation. As shown in the table, raw IoT-derived data are progressively refined through mapping, aggregation, and contextualisation steps to support monitoring, analysis, and planning-oriented decision support.

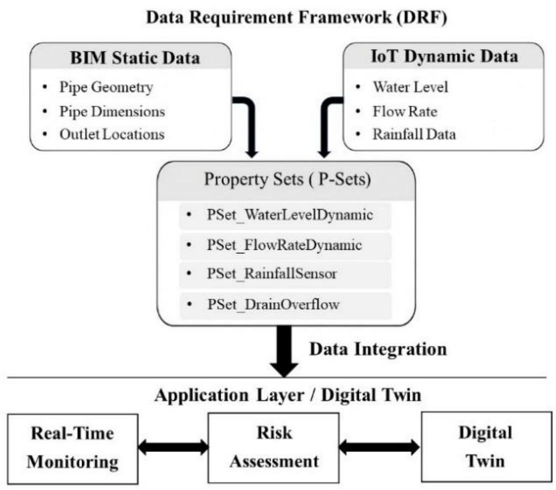

Figure 4. Building Information Modeling–Internet of Things (BIM–IoT) data integration through Property Sets (P-Sets) under the Data Requirement Framework (DRF)

Table 6. Data flow under the Data Requirement Framework (DRF)

Step	Layer	Data Source / Input	Main Process	Data Output
1	IoT Dynamic Layer	Sensor data (water level, flow rate, rainfall, overflow status)	Time-series data acquisition	Raw dynamic data
2	Integration Layer	Raw dynamic data	Data validation and consistency checking	Validated data
3	Integration Layer	Validated data + BIM static data	Data transformation and mapping via P-Sets	BIM-linked dynamic attributes
4	Integration Layer	BIM-linked attributes	Data aggregation and preparation for analysis	Decision-ready data
5	Application Layer	Decision-ready data	System status analysis and abnormal event detection	Alerts / risk assessment results
6	Application Layer	Analysis results	Visualisation and decision support	Dashboards, alerts, digital twin inputs

Notes: IOT: Internet of Things, BIM: Building Information Modeling, P-Sets: Property Sets

Table 6 summarises the data flow processes under the proposed DRF, illustrating how IoT-derived time-series data are validated, mapped to BIM elements through P-Sets, and transformed into decision-ready information for application-level use.

The results presented in Table 6 indicate that the DRF provides a structured and coherent pathway for managing heterogeneous data types without modifying the core BIM data structure. By explicitly defining data flow stages and responsibilities across architectural layers, the framework reduces data fragmentation and enhances the consistency of integrated information.

To further illustrate the overall data movement and interaction between DRF layers, the conceptual data flow under the proposed framework is presented in Figure 5. The figure highlights how dynamic data from the IoT layer is processed through the Integration Layer and prepared for application-level analysis while maintaining linkage to BIM elements.

By demonstrating a structured pathway for data transformation and utilisation, the data flow modeling results confirm the functional coherence of the proposed DRF architecture. These results provide a basis for evaluating the architectural readiness of the framework, which is further examined through conceptual validation results in Section 4.6.

For conceptual evaluation, "Meets" indicates that all required architectural and data integration conditions were addressed within the corresponding DRF layer. "Partially meets" indicates that approximately 50–80% of the expected conditions were addressed within the current conceptual scope but may require further implementation-level refinement.

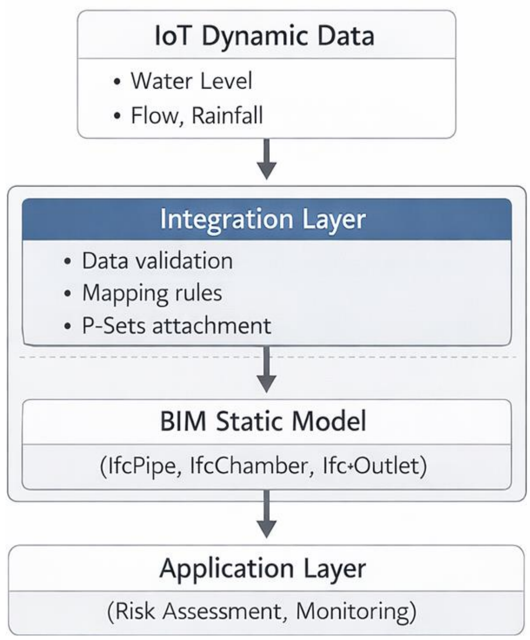

Figure 5. Data flow modeling under the proposed Data Requirement Framework (DRF)

Table 7. Conceptual validation matrix of the DRF

DRF Layer	Structural Consistency	Data Completeness	Integration Feasibility	Remarks
BIM Static Layer	Meets	Partially meets	Not applicable	Provides geometric and topological consistency but lacks dynamic representation
IoT Dynamic Layer	Meets	Meets	Partially meets	Captures operational states but requires structured linkage to BIM elements
Integration Layer	Meets	Meets	Meets	Enables validation, mapping via P-Sets, and semantic alignment
Application Layer	Meets	Partially meets	Meets	Supports monitoring and analysis; full operational deployment not yet implemented

Notes: DRF: Data Requirement Framework, BIM: Building Information Modeling, IOT: Internet of Things, P-Sets: Property Sets

As shown in Table 7, the Integration Layer achieves the strongest validation outcome because it satisfies structural consistency, data completeness, and integration feasibility. The BIM Static Layer and Application Layer partially meet the data completeness criterion because they depend on future operational data and implementation-level deployment. The IoT Dynamic Layer partially meets integration feasibility because dynamic monitoring data requires a structured linkage to BIM elements through the Integration Layer. These results indicate that the proposed DRF is conceptually coherent, while further empirical implementation is still required.

The conceptual validation examines three key aspects: structural consistency, data completeness, and feasibility of data integration across the DRF layers. Structural consistency is evaluated by examining the alignment between BIM static data, IoT dynamic data, and customised P-Sets within the Integration Layer. The results indicate that the proposed framework maintains consistent relationships between data entities, enabling dynamic operational data to be associated with corresponding BIM elements without modifying the core BIM data structure.

Data completeness is assessed by examining whether the defined data requirements sufficiently represent key operational conditions of building rainwater drainage systems. The results confirm that the combination of BIM static data and IoT dynamic data requirements captures both physical system characteristics and time-dependent operational behaviour, thereby addressing the critical data gaps identified in Section 4.3.

The feasibility of data integration is evaluated through the logical consistency of data flow and data linkage mechanisms under the DRF architecture. The validation results demonstrate that the proposed framework provides a coherent pathway for transforming heterogeneous data into integrated, decision-ready information suitable for monitoring, risk assessment, and planning-oriented analysis.

Overall, the conceptual validation results indicate that the proposed DRF is structurally consistent and architecturally ready for future implementation and extension toward digital twin development. While no physical sensor deployment or real-time system testing is conducted in this study, the validation demonstrates that the framework provides a robust and scalable foundation for subsequent empirical studies and sustainability-oriented planning applications.

4.6 Transferability of the Data Requirement Framework

Although the proposed DRF was developed and examined in the context of building-scale rainwater drainage systems, its architectural structure is not limited to drainage applications. The identification of dynamic variables such as water level, rainfall intensity, and overflow status is drainage-specific; however, the layered integration logic, structured data gap analysis approach, and IFC-aligned customised P-Set extension mechanisms are transferable to other building systems requiring time-series integration.

Specifically, the four-layer architecture (BIM Static Layer, IoT Dynamic Layer, Integration Layer, and Application Layer) can be applied to HVAC systems, water supply networks, energy monitoring systems, and other infrastructure domains where static design information must be linked with dynamic operational data. The drainage-specific variables may change, but the schema-level extension logic and temporal data structuring strategy remain reusable.

This transferability demonstrates that the proposed DRF functions as a scalable data architecture rather than a single-use case framework, while still maintaining domain-specific precision in the present study.

5. CONCLUSION

This study proposed a DRF to support systematic integration of BIM and IoT data for sustainable planning and management of building rainwater drainage systems. The framework was developed to address structural limitations of conventional BIM in representing dynamic operational behaviour and to reduce fragmentation between static design information and time-series monitoring data.

By identifying BIM static data and defining IoT dynamic data requirements, the study revealed critical data gaps that hinder effective system monitoring and risk assessment. The results demonstrated that these gaps arise primarily from the inability of standard BIM data structures to accommodate time-dependent information rather than from deficiencies in geometric or material representation. To address this issue, customised P-Sets were developed as a structured mechanism for linking dynamic operational data to BIM elements without modifying the core BIM schema.

The proposed DRF integrates BIM static data, IoT dynamic data, and P-Sets within a four-layer architecture comprising the BIM Static Layer, IoT Dynamic Layer, Integration Layer, and Application Layer. Results from data flow modeling and conceptual validation confirmed that the framework provides a coherent and scalable foundation for managing heterogeneous data and transforming it into decision-ready information. This capability supports planning-oriented analysis, system monitoring, and preparation for future digital twin development.

Overall, the study contributes a data-centric and framework-based approach to BIM–IoT integration for building rainwater drainage systems. By focusing on data requirements and architectural readiness, the proposed DRF enhances the capacity of digital building models to support resilient and sustainable drainage planning under increasing rainfall variability and climate-related uncertainty.

Despite the structured development and conceptual validation of the proposed DRF, several limitations should be acknowledged. First, the validation is conceptual and does not involve empirical testing through real-time sensor deployment or operational performance measurement. Second, the framework has not yet been implemented in a live building environment to assess system integration challenges under practical constraints. Third, the study does not evaluate computational overhead, data processing latency, or system scalability under large-scale deployment conditions. Finally, the framework relies on IFC-based schema extension mechanisms, which may not be uniformly supported across all BIM authoring platforms. These limitations indicate the need for subsequent empirical implementation and performance-based evaluation to advance the DRF from architectural readiness toward operational deployment.

6. FUTURE WORK

Although this study focuses on conceptual framework development and validation, several directions for future research can be identified. First, the proposed DRF can be applied and evaluated through real-world implementation using IoT sensor deployment in building rainwater drainage systems to assess its performance under actual operational conditions. Such studies would enable quantitative evaluation of data integration effectiveness and support refinement of data requirements.

Second, the DRF may be extended to support predictive analysis by integrating hydraulic or hydrological models with real-time monitoring data. This extension would enhance the capability of the framework to support early warning, risk forecasting, and adaptive drainage management.

Finally, future research may explore the application of the DRF within a full digital twin environment, including automated data updating, system simulation, and decision-support tools for long-term sustainability planning. These extensions would further strengthen the role of BIM–IoT integration in resilient building and infrastructure management.

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