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Research article

Enhancing strategic decision-making in built asset management through BIM-Enabled asset information modelling (AIM) for public buildings in Ethiopia: A fuzzy-AHP analysis

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ABSTRACT

BIM-Enabled Asset Information Modelling (AIM) entails incorporating extensive data, known as big data, into digital platforms for informed decision-making. However, the lack of accurate and reliable data and the immaturity of BIM integration in existing buildings lead to operational phase performance inefficiencies due to inadequate data access. A strategic approach using BIM-enabled AIM is proposed to address these challenges, with the goal of enhancing data accessibility and adequacy for the operational team's performance. This study aims to develop a framework of information requirements that supports operational strategic decisions in asset portfolio management. To develop the framework, we employed a methodology that combines the Analytic Hierarchy Process (AHP) a structured technique for organizing and analysing complex decisions with fuzzy logic, which helps handle uncertainty in experts' judgments. A comprehensive questionnaire based on the Analytic Hierarchy Process (AHP) methodology was developed to gather expert insights on prioritizing information requirements, and it was administered to 11 experts selected for their diverse expertise in problem area. Cost, risk, and business value as selection criteria, while technical, managerial, financial, legal, and commercial categories of information are considered as alternatives in the AHP hierarchy. Utilizing the described methodology, fuzzy-AHP analysis revealed distinct variations in information requirements across the strategic decisions of maintain/keep, improve/adapt, and deconstruct/disassemble. For decisions on whether to maintain/keep buildings, the primary information requirement is managerial (39.6 %), followed by legal (20.7 %) and commercial (20 %), guiding strategic decisions. In contrast, improve/adapt decisions prioritize technical information (39 %), with financial (15.5 %) and legal (13.5 %) considerations also being significant. For the deconstruct/disassemble decisions, technical information requirements are most critical (55.5 %), followed by legal (16.6 %) and commercial (12.8 %) information. The findings highlight the need for tailored data generation strategies in existing buildings to address specific decision requirements, aiding in planning and resource allocation towards efficient AIM. The primary limitation of this study is its reliance on a small pool of 11 experts, which may limit the generalizability of the findings. Future research should aim to broaden the expert base to enhance the applicability and robustness of the results.

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1. Introduction

Emerging trends in digitization have significantly transformed the traditional asset lifecycle management practices of the Architecture, Engineering, Construction, and Operations (AECO) industries. These innovations are steering the industry towards a more future-oriented and innovative approach. The integration of state-of-the-art digitization methods, such as Building Information Modelling (BIM), Artificial Intelligence (AI), the Internet of Things (IoT), Laser Scanning (LS), Linked Data(LD), Digital Twin (DT), Virtual Reality (VR), and Augmented Reality (AR), is becoming increasingly essential in enhancing asset/product lifecycle management. These technologies are crucial in driving data-driven decision-making and automating processes, which not only boosts efficiency and accuracy but also fosters innovation, enabling AECO sectors to meet the growing demands of modern infrastructure and buildings [1–3].

The innovative methods have shown improved performance for the design and construction phases of an asset lifecycle. However, despite the evident benefits of the digital methods, particularly in the early phases, the application in the post-construction phase of built asset management remains underexplored and insufficiently integrated [4]. Most existing buildings, constructed before the advent of the technologies, are yet to fully leverage the advancements to optimize long-term value, particularly in a resource-constrained environments. However, digitizing existing buildings can significantly enhance access to reliable and accurate information for operation and maintenance and boost the informed decision-making process [5–7].

Organizations often struggle with capturing, storing, and validating data across a diverse and complex asset portfolio, leading to uncertainty about what information should be collected for efficient asset management [8]. This challenge is exacerbated in developing countries, where built asset management is often overlooked despite its critical importance in maintaining optimal building performance, meeting service requirements, and addressing environmental sustainability. Booty [9] highlighted that 90 % of built asset management (BAM) functions rely heavily on information logistics and management. In this context, digitization plays a crucial role in addressing and mitigating the challenges associated with effective information management, offering streamlined processes and improved data handling capabilities. While digitization has shown promising results in the initial phases of an asset's life cycle, its benefits are underexploited in the operation and maintenance phase, which is the longest and most capital-intensive stage.

As digital data becomes a critical input in the asset digitization process, maintenance strategies are evolving rapidly. As a result, there is shift in moving away from traditional reactive models toward more advanced, AI-driven, and human-centric approaches [12]. These new methodologies not only predict future needs but also focus on efficiently generating and using digital data. As a result, adopting these forward-looking approaches is increasingly essential and inevitable in modern built asset management. The digitization of these assets can only be achieved by delivering accurate and reliable data. Nevertheless, the major challenge is the lack of the digital data in AIM that can serve as a single source of truth in decision-making [12]; [4,13].

This circumstance is particularly pronounced in the context of the present study, where the management of existing buildings predominantly adheres to traditional and manual data management approaches, where digital data is unavailable.

To enhance the efficiency of delivering digital data for the development of asset information modelling, prioritizing information requirements is of paramount importance. This strategic focus ensures that the most critical data is accurately identified, streamlined, and integrated, thereby optimizing the overall process, and contributing to more effective asset information modelling.

Thus, the main aim of this study is to develop a prioritized information requirements framework for BIM-based asset information modelling (AIM). This framework focuses on an optimized approach guided by strategic, operational phase decisions. Strategic decisions during the operational phase in asset portfolio typically fall into three main categories: maintaining the current state, improving, or adapting, and deconstructing or disassembling buildings. For effective digitization of existing buildings, delivering accurate and reliable data efficiently is essential. However, generating all information from existing buildings is not practical, as it is costly, time-consuming, and requires specialized expertise. Therefore, an optimized approach is necessary, prioritizing the delivery of the most critical information required for informed decision-making based on well-defined criteria.

Therefore, a clear set of steps is required to ensure the consistent and coordinated delivery and management of information for data-driven decision-making in asset management.

First, defining asset information requirements (AIR) is essential to ensure the required type and level of detail in the data to be delivered.

Second, managing the quality of big data (in terms of accuracy, completeness, validity, consistency, uniqueness, timeliness, and fitness for purpose) is an important factor as it requires adequate management, processing power, and storage capacity when it comes to digitization [14]; [13].

Third, efficient asset information modelling (AIM) demonstrates the value it can generate through concrete projects triggered by business requirements [15].

Thus, this study develops a requirement framework for information for efficient and optimized built asset information modelling that enhances informed decision-making practices in existing buildings.

In this regard, the study contributes to the development of efficient and optimized built asset information modelling, especially for existing buildings on based strategic decisions within the asset portfolio in organizations.

The remainder of this article consists of five parts: Section 2 discusses the state of the art and research gap in the domain; Section 3 describes the research design and methodology; Section 4 presents the results of the study; and Section 5 presents discussions based on results; followed by a conclusion in section 6.

2. State-of-the-art and research gap

2.1. Information requirements in BIM-enable asset information modelling

Defining operational information requirements is a significant challenge for asset owners seeking to implement effective BIM-Enabled built asset management [13]. The significance of these requirements in addressing the complexities of built asset operations and project delivery is evident. To tackle these challenges, it is essential to focus on standards, practical methodologies, and the efficiency of BIM applications in the context of built asset information modelling (BAIM).

However, the use of BIM in asset operations presents notable difficulties, particularly concerning the reliability, interoperability, and usability of information. The complexity of implementing BIM in large organizations is further compounded by the challenge of identifying and formalizing the information requirements necessary to support both model-based project delivery and asset management [16].

Recent standards, such as the EN ISO 19650 series, have been introduced to assist in the development of the critical information requirements for BIM-Enabled AIM [17]. The Level of information requirements framework, in particular, provides a structured approach in defining the extent and granularity of these requirements. In the operational phase, asset information requirements (AIR) within asset information modelling (AIM) play a vital role in ensuring effective asset management. Yet, the potential of BIM during this phase has often been limited by the difficulties in developing information requirements that adequately support the BIM process [1]. Specifically, Heaton & Parlikad [1] highlighted the challenges many organizations face in deriving asset information requirements (AIR) from broader organizational information requirements (OIR).

Therefore, establishing an effective and efficient information system infrastructure is crucial. Such an infrastructure must be capable of capturing, interpreting, storing, and reporting operational information to fully leverage the benefits of BIM in asset management.

2.2. Prioritization of asset information requirement

Prioritizing AIR is crucial for developing efficient AIM, as it underpins effective asset management practices by ensuring that the most critical information is addressed first. Prior studies have focussed the importance of defining asset information requirements and its modelling for effective O&M performance [18,19].

However, the type and level of detail of information required through the life cycle process vary significantly. For instance, Carbonari et a (2015) stated that as the asset/product moves from inception to operation and maintenance phase, the need for graphic information decreases while demand for attribute information increases. While, RIBA [20] and ISO [21] are also concerned about the same issue, there is a lack of scientific research on the value given to data in decision-making in the O&M phase in terms of the specific purpose for which the information is to be used. The lack of clearly defined formal information requirements greatly hinders the creation of an AIM that is truly fit for purpose, emphasizing the critical need to establish and communicate these requirements from the outset [22].

Thus, efficient approaches for quality data provision and identification of information requirements need to be purpose-oriented to support owner and operator decision-making processes. In this study, the concepts of maintaining, improving, and deconstructing built assets are framed as strategic decisions made during the operational phase of asset management [23–25]. Similarly, Seeley [26] defines building maintenance or operational phase decisions on buildings as the actions undertaken to preserve, restore, or enhance all components of a building including its services and surroundings to meet current acceptable standards, thereby sustaining the building's utility. This holistic approach emphasizes the importance of continuous management to extend the lifecycle and functionality of built assets. Accordingly, decisions on buildings mainly consists of three primary components: ***servicing, rectification, and replacement***. These components are regarded as strategic decisions, and the information requirements framework need to be aligned with these objectives to develop a purpose-driven AIM efficiently.

Moreover, there is a lack of studies on the ideal specificity and type of information and composition for the strategic decisions in built-asset management that supports the definition of information requirements with a defined set of criteria in AIM. The systematic process of Multi-Criteria Decision-Making (MCDM) methods can be used to prioritize the information most important to the business case of the owner.

Hence, this prioritization in the present study is structured based on criteria that align with the strategic decisions in owner organization derived from the value model in asset management standard [27,28].

Furthermore, a significant challenge identified in this study context is the difficulty faced by the operational team in acquiring accurate and reliable data on built assets, which is essential for informed decision making in built-asset management (BAM). This matter underscores the complexities inherent in data collection processes and highlights the need for robust data management practices to support effective decision-making in the operational phase of BAM. Subsequently, the O&M team in public buildings demanded to have almost all categories of information for buildings of varying conditions and decisions within the asset portfolio including technical (T), managerial (M), financial (F), legal (L), and commercial (C), which seems difficult to achieve due to limitations on expertise, time, cost, technology, and effort. In response to this challenge, the study hypothesizes that the various categories of information requirements do not hold equal importance, nor do they share similar levels of detail and composition across the three strategic decisions associated with the operational phase, as described by [10]. This hypothesis aims to address the nuanced differences in information needs, suggesting that strategic decision-making in built-asset management requires a tailored approach to data utilization. This approach also significantly increases the efficiency of the information generation process in resource-constrained contexts [29].

In the subsequent sections, three key strategic decisions of the operational phase are described to illustrate how a purpose-driven definition of information requirements improves BAM performance.

2.3. Operational phase strategic decisions in built asset management

An oft-cited definition of FM or operational phase functions in buildings is given by Barrett and Baldry [30] as an integrated approach for an organization to ***operate, maintain, improve, and adapt its building infrastructure***. According to this definition, asset owners and their representatives prioritize these three key functions to achieve organizational objectives. This is mainly because,the O&M phase is typically where a large portion of the whole life cycle cost is incurred, and the stage represents a significant opportunity for cost efficiencies [8,31].

Decisions or interventions made at different levels in built asset management do not require all information in the same detail, quality, and complexity [32]. For the purpose of the present study scope, operational phase decisions are grouped into three main categories: maintain/keep, improve/adapt, and deconstruct/disassemble [11].

2.3.1. Maintain/keep (M/K) decision

Maintain/keep (M/K) refers to the operation and maintenance phases' strategic decision to any action taken in the form of corrective, preventive, a proactive, predictive strategy to keep, retain, or restore the building and its components to make them suitable for the purpose as originally designed [33]; [9,25,34].

2.3.2. Improve/adapt (I/A) decision

Building adaptation or improvement is defined from diverse perspectives, Wilkinson et al [35] described it as change of use, maximum retention of original structure and fabric, and extending useful life taking concepts from diverse sources. Furthermore, building improvement/adaptation is also defined as any intervention used to adjust, reuse, or upgrade a building to suit new conditions or requirements [33]; [36]. In the context of building improvement/adaptation, numerous terminologies such as refurbishment, retrofitting, rehabilitation, renovation, restoration, modernization, conversion, adaptive reuse, and conservation are frequently used interchangeably. However, these terms can generally be categorized under the broader concepts of improvement and adaptation, reflecting various approaches to enhancing the functionality, performance, or lifespan of built assets beyond original design specifications [37].

Although improving/adapting sounds similar to maintaining/keeping strategic decisions, the principle is distinguishable from conversion, rehabilitation, and refurbishment, which have a clear objective of adapting or increasing the utility of a building rather than maintaining it at the existing level.

In certain scenarios, the decision to improve a building may be necessary to maintain or keep its value. For example, if a building becomes unsuitable for its intended purpose due to outdated technology or changes in performance requirements [25]. Or if a building exhibits poor adaptability, it is likely to remain inefficient and fail to meet the functional requirements necessary for its intended core business purposes. This lack of adaptability can hinder the building's ability to respond to changing needs, thereby compromising its overall performance and utility. In such situations, a building owner need to decide either to improve or find another building and abandon the existing one, where the building can be considered for another use, deconstructed, or demolished [38].

2.3.3. Deconstruct/disassemble (D/D) decision

Deconstruction/disassembling refers to the whole or partial disassembly of buildings to facilitate component reuse and material recycling to eliminate demolition by recovering reusable materials. It can be difficult for existing buildings to implement the principle of circular construction using design for improving/adaptability, as this concept only gained popularity in the late 1990s [39]. For the concept to be applicable, building information modelling (BIM) can play a considerable role in decision-making through knowledge of a building and its associated information.

For this reason, building owners and their representatives need to know the most important information about a building before deconstruction. This approach contributes to environmental sustainability concerns since reusing or renovating a building can have savings between 4 and 46 % compared to a new building [40]. However, important information is required for safe demolition modelling if a building is to be demolished for a valid reason. Therefore, this scenario underscores the critical importance of establishing an efficient AIM to facilitate easy access to accurate and reliable information, thereby supporting informed decision-making. An effective AIM plays a pivotal role in enhancing data accessibility and quality, which are essential for optimizing strategic decisions in built-asset management.

2.4. Selection criteria for required information

To support the above-described decisions with relevant information, three criteria are defined from the asset management value model principle. The effectiveness of asset management decisions depends on selecting initiatives or criteria that align with organizational goals. This involves understanding the requirements of an organization, from concept to disposal, and addressing complexities to services, including reliability, safety, timeliness, and cost-efficiency. In addition, good practices in data collection, recording, and analysis using user-friendly information systems are essential for risk-informed and value-driven decision-making [41].

The three enablers of value towards optimized asset performance include cost, business value, and risk [28]. These enablers are considered criteria for selecting the most appropriate information categories for organizational effectiveness in the present study. The integration of the value model with the information requirements and value enablers (criteria) is illustrated in Fig. 1.

The value model of asset management is an example standard that focuses on the importance of balancing cost, risk, and business values to optimize the use of assets and achieve maximum value for organizational objectives. Adopting ISO 55000 and ISO 55001 standards helps organizations better manage their assets, enhance efficiency and effectiveness, and comply with regulatory frameworks [42]. BIM is one of the best valuable platforms towards improved performances in asset management. Business value requires a concerted effort to identify critical activities and decisions to continuously improve to an advanced stage of maturity [13]. Streamlining BIM with asset management systems and capturing information from physical assets can help organizations derive value from BIM investments and improve maintenance and repair options, leading to a reduction in maintenance and operating costs [43,44].

2.4.1. *Cost criterion*

The operation and maintenance phase represent the most substantial portion of an asset's life cycle costs. The cost portion constitute a significant share of the overall life cycle expenditure of a product. Given that most buildings are designed to last for decades, the cumulative maintenance costs throughout a asset's life cycle become notably significant for the owner [45].

Moreover, O&M is a phase where strategic asset investment decisions considerably impact the life cycle costs. The cost criterion also considers how important a particular piece of information is to improving cost efficiency in strategic decisions. Moreover, cost criterion also accounts for cost efficiency in generating specific categories of information for strategic decisions for the remaining lifetime of an existing building. Thus, effectively managing a asset's operational costs and performance over its service life can provide significant financial benefits.

2.4.2. *Risk criterion*

Information is required to support risk management, especially for identifying and reviewing risks to which a building could be exposed, such as natural hazards or extreme events. This information includes things such as asset replacement value for insurance purposes. Risk appetite shall be considered when evaluating risk alignment with stakeholders. BIM-AIM is an important integration in managing risk in asset management as it utilizes risk-based management methods to ensure reliability, safety, and environmental protection [46].

As stated in Alirezaei et al. [47], BIM enables online inspection of project risks and provides informed risk-related solutions by

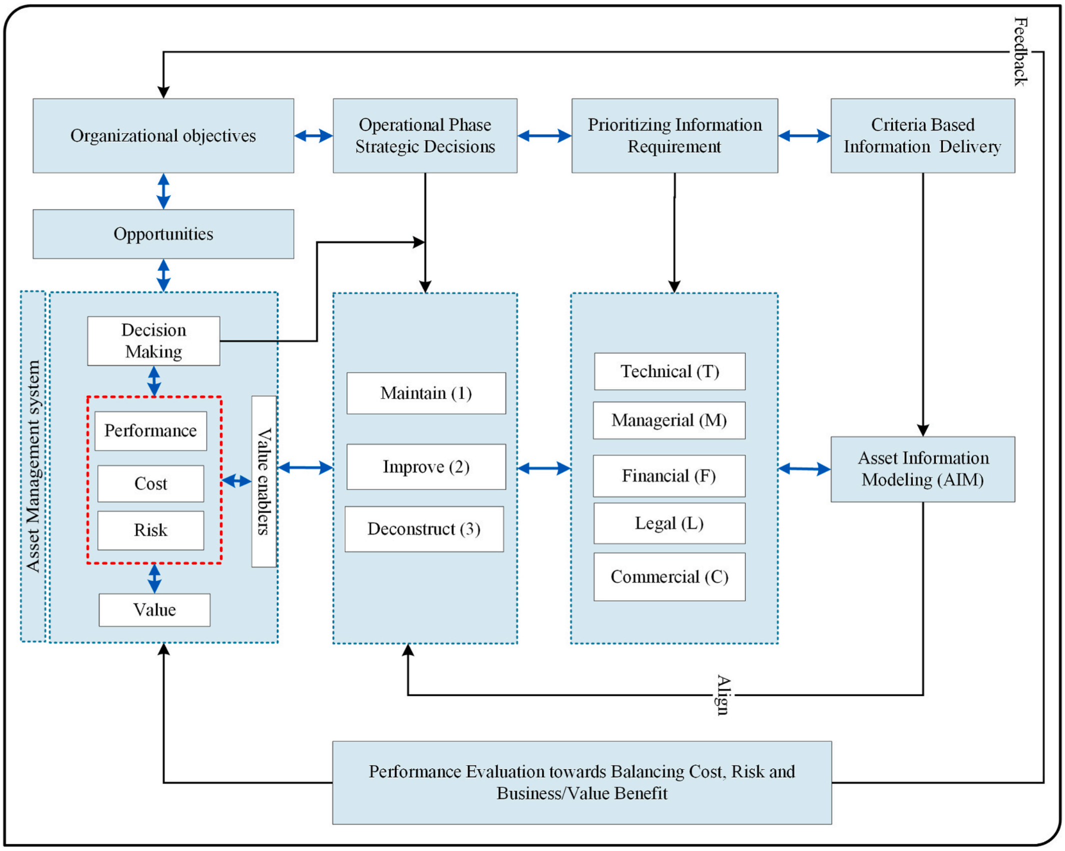

Fig. 1. Integration BIM-AIM based on (ISO 55000. ISO1960-3).

enhancing data quality and minimizing risk in asset management [48]. Moreover, risk is one of the primary components of a value model to optimize maximum value for asset performance.

2.4.3. Business value criterion

The BIM-based AIM can help asset owners by improving asset data delivery, operations, and maintenance practices, leading to better asset management and business value realisation [13,27,28,49–51]. This criterion refers to identifying the information required to achieve the business goals (productivity, faster decision-making, efficient maintenance, data-driven operations, customer service, safety, profit growth, and sustainability) in a way to demonstrate business value realisation. Moreover, it is a business value that BIM-based AIM brings to an owner in choosing the most valuable information requirement for specific strategic decision.

2.5. The alternatives (information requirements)

At the lowest level of the AHP hierarchy, a list of alternatives provides decision points evaluated using criteria for strategic decisions in the hierarchy. The alternatives presented in the hierarchy comprise five categories of information (technical, managerial, financial, legal, and commercial) as shown in Table 1 and Fig. 1. The alternatives are information requirements defined in ISO -19650-3 for BIM-enabled AIM for operational phase decision-making. A brief description of each information requirement is provided based on [7,18,27] as follows.

2.5.1. Technical (T)

This information category includes both graphical and non-graphical data about an asset/a product. It includes, but is not limited to, asset classification, engineering data, design parameters, operational data, commissioning logs and data, performance characteristics and design limits, the specification of the project platform (e.g., CDE), and the specification of the data format (e.g., IFC, COBie).

2.5.2. Managerial (M)

Managerial information requirements include but are not limited to asset type, asset condition, asset location, maintenance schedule, warranties, end of warranty period, destination of an asset, end-of-life cycle process, access scheduling, work schedules, historical records of maintenance tasks, schedule of maintenance and inspection tasks, qualifications/certifications required for each task, hazardous content or waste information, emergence plan details, historical asset failure details, etc.

2.5.3. Financial (F)

Financial information refers to the initial capital, maintenance and operational costs, replacement value, refurbishment, and conversion measures in its life cycle process. These requirements are designed to ensure consistent, reliable financial data management, improving transparency, cost control, and long-term asset performance.

2.5.4. Legal (L)

Legal information in identifying information requirements for built AIM includes but is not limited to, ownership details, maintenance demarcation, contractual information, property boundaries, work instructions, legal obligations, and health and safety requirements. These requirements ensure that AIM supports robust legal governance, minimizes risks, and maintains accountability across the asset lifecycle.

2.5.5. Commercial (C)

The commercial information requirement includes but not limited to description and role of installation/manufacturer/supplier address details, spare parts details, installation time (lead time details), list of people at commissioning (internal and external), status, benefits, and performance targets (e.g., intensity of use, performance standards) and checking for the presence of sensitive or critical equipment.

To develop a requirement framework of information prioritization, the study utilized the performance enablers of the "***value model***’’ as criteria for evaluating the degree of importance of the five information categories to each operational strategic decision. To this end, a fuzzy-AHP approach is employed to select the most important information requirements based on defined strategic decisions. This approach promotes structuring and defining information requirements for specific strategic decisions about relevance by

Table 1
Hierarchy of AHP problem.

Levels			
0	1	2	3
Goal	Criteria	Decisions	Information
Prioritization of Information Requirements			Technical (T)
	Cost (A)	Maintain/Keep (1)	Managerial (M)
	Risk (B)	Improve/Adapt (2)	Financial (F)
	Business Value (C)	Deconstruct (3)	Legal (L)
			Commercial (C)

excluding less important information for efficient AIM.

2.6. Motivation and research gap

The built asset information management (BAIM) in the present study context is largely entrenched in traditional paper-based filing, which is subject to data loss and compromised reliability, accuracy, and completeness of data, which causes wastes of remarkable time in searching these manual files. This approach hinders easy access to relevant asset information for the operations team, impeding knowledge based effective decision-making processes. As stated in the preceding sections, the post-construction stage O&M in the study context, currently operates at a lower maturity level. Transitioning to a robust IT-based BAIM practice holds promise in overcoming these hurdles and facilitating data-driven decision-making.

Thus, the present study aims to provide valuable insights into increasing the maturity of IT-based BAIM practices using BIM with a particular emphasis for the context. Furthermore,there is significant underdevelopment in the integration of BIM with the operational phase of built assets, especially in public buildings in developing countries such as in Ethiopia. While previous studies have explored the importance of state-of-the-art digitization for a data-driven operational phase decisions, there is a notable lack of comprehensive research focused on optimizing and structuring information requirements for BIM-enabled BAIM. This gap in the literature justifies the need for the present study, which aims to fill the gap by prioritizing and structuring the critical information requirements for efficient BIM-AIM integration based on strategic decisions in built asset portfolio management.

Given the widespread challenges in digitizing-built assets such as the high costs, time requirements, and need for specialized expertise, the present study is motivated by the requirement to rationalize and optimize the information requirements tailored for strategic decisions for existing buildings.

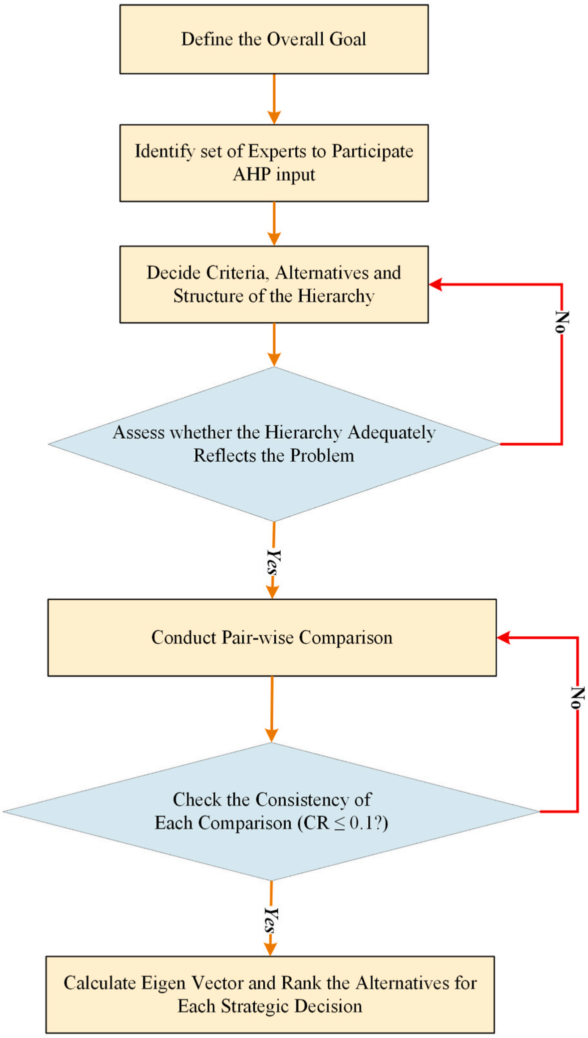

Fig. 2. Overall process of the AHP method.

3. Study design and methods

3.1. Study design

Multi-criteria decision making (MCDM) aims to analyse, support, and comprehend decisions in situations where multiple criteria towards single objective exist. MCDM is defined as the process of identifying a set of alternatives and selecting optimal solution based on relevant criteria [52–55]. Two types of MCDM exist: multi-objective decision-making (MODM) and multi-attribute decision-making (MADM).

A MODM problem in one hand involves infinitely many decision arguments and consequently, many objective functions. MODM is naturally associated with mathematical programming issues when dealing with optimisation. While the MADM method, on the other hand, is used to solve problems with discrete decision spaces and limited alternatives [56]; [57–59]. Human judgment and involvement are crucial in MADM in contrast to MODM techniques. The present study employs MADM using cost, risk, and business value as criteria to select the most critical information requirement corresponding to strategic decisions.

3.2. Analytical hierarchy process

The Analytic Hierarchy Process (AHP) is a widely used MCDM method that helps decision-makers prioritize and evaluate complex options based on multiple criteria. By structuring decisions into a hierarchy and using pairwise comparisons, AHP facilitates a systematic and quantitative analysis of preferences, leading to informed and consistent decision outcomes.

According to Saaty [60], AHP is a pairwise comparison and a matrix-based analysis. It is one of the most commonly used multi-criteria decision analysis techniques that helps to solve multiple complex decision problems. The AHP-MCDM method uses Eigen value approach to conduct pairwise comparison and provides a methodology to calibrate numeric scale for measurement of quantitative and qualitative performances [61]. AHP as a MCDM method is based on a layer of hierarchical structure separated into various layers designed from level 0 to level n.

Two approaches are applicable in structuring an AHP decision problem, either through bottom up or top-down. Both bottom-up and top-down approaches can be used to develop a decision hierarchy and evaluate the relative importance of criteria and alternatives. However, a bottom-up approach starts with identification of the specific alternatives or criteria and then working upward to determine the relative importance of each criterion and alternative.

This approach is useful when the decision problem is complex, and the decision-maker needs to understand the underlying structure of the problem. In this approach, the decision maker first identifies the alternatives and then the criteria that will be used to evaluate them. In both cases, the goal of the decision problem is normally placed at the top of a hierarchical model [62]. The process followed in analysing the present problem is shown in Fig. 2.

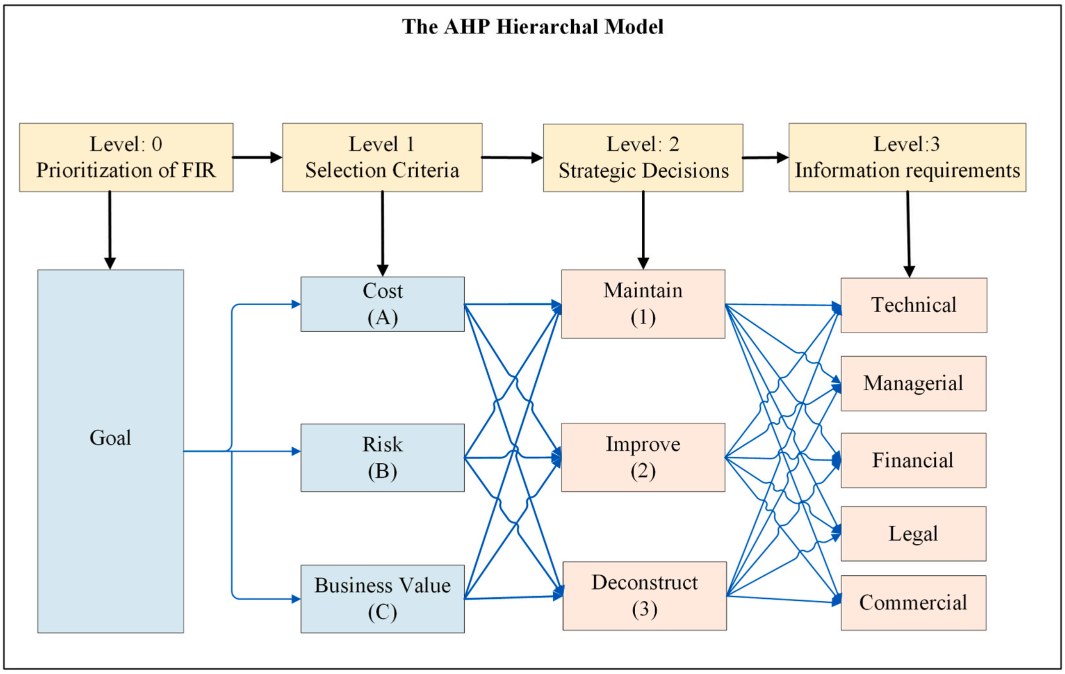

Fig. 3. Hierarchy of AHP problem.

3.2.1. Incorporating fuzzy logic in AHP

Incorporating fuzzy logic into AHP enhances decision-making in complex multi-criteria situations by addressing the inherent uncertainties and ambiguities of human judgment. The fuzzy-AHP approach utilizes fuzzy set theory, allowing decision-makers to express preferences using linguistic terms that are subsequently converted into Triangular Fuzzy Numbers (TFNs) for pairwise comparisons [63,64]. This method simplifies the creation of pairwise comparison matrices and improves the precision of priority weight calculations, thereby providing a more detailed assessment of alternatives [63].

By integrating fuzzy logic with AHP, the process becomes more adaptable and realistic, leading to more informed decisions in various fields such as supply chain management and facility layout planning [65]; [66]. Fuzzy logic represents an innovative approach to decision-making, effectively managing the uncertainties and vagueness often present in real-world scenarios [38]; [62,67]. Unlike conventional logic, which is restricted to binary true or false values, fuzzy logic offers a spectrum of truth values, enabling nuanced interpretations and effective handling of complex situations.

A triangular fuzzy set is employed in the present study to address the uncertainties and ambiguities in expert responses to the AHP questionnaire, transforming crisp values into a fuzzy membership function function [68–70]. This approach facilitates a more reliable and nuanced evaluation of expert judgments, enhancing the overall robustness of the decision-making process.

3.2.2. Steps in fuzzy AHP analysis

As a multi-criteria decision analysis technique AHP employs a hierarchical and pairwise comparison matrix. This technique facilitates the resolution of multiple intricate decision problems. In utilizing AHP, a hierarchical structure is typically subdivided into various layers, ranging from level 0 to level n. Where n refers to the number of layers. The aim of the decision problem is conventionally positioned at the top of the hierarchical model. The remaining levels of the structure comprise categories, factors, alternatives, and other relevant components [71]. Saaty criticized the application of fuzzy sets to AHP analysis in his work [72]. However, due to many advancements in applying fuzzy sets for AHP problems, its application became common in MCDM. This is mainly because a single element or value is insufficient to model real-life problems due to the vagueness and uncertainty of human evaluation. The steps followed in analysing the Fuzzy AHP problem in the present study are briefly described as follows:

- Step 1: Analysing Problems

AHP model developed for the study comprises four successive levels, as shown in Table 1 and Fig. 3. The top level of the hierarchy (Level 0) is the goal of the model, which is “Prioritization of information requirements for decision support in strategic decisions”. The second level (level1) of the hierarchy is the criteria (cost, risk, and business value) for selecting information categories based on the major strategic decisions in O&M phases. The third level (Level 2) refers to strategic decisions (maintain/keep, improve/adapt, and deconstruct/disassemble) of an asset portfolio. The fourth level (Level 3) is the alternatives, consisting of five categories of information requirements relevant for efficient AIM.

- **Step 2: Construct a Hierarchical Model**

Construct a hierarchical structure involving the goal, criteria, the strategic decisions, and alternatives to apply the fuzzy-AHP (FAHP) approach. The relationship among criteria, strategic decisions, and alternatives are defined and mapped as shown in Fig. 3. The first level of the hierarchy is represented by a goal to prioritize information requirements based on strategic decisions. The second level represents the criteria (Cost, risk, business value). The third level represents strategic decisions for which information is required (maintain, improve, and deconstruct). Finally, the bottom level represents five alternative of information requirements.

- Step 3: AHP Questionnaire Design and Survey

An AHP questionnaire was structured, designed, and pilot-tested before being used for data collection. A total of 20 purposely

Table 2
Expert profiles participated in decision-making.

No.	Position	Experience (Year)	Academic Achievement	Educational Background	Organization
1	General manager	15	PhD	Civil Engineering	Electro-mechanical & Research
2	Ass. Professor	15	PhD	BIM and Architecture	Consultant Researcher
3	Ass. Professor	18	PhD	Construction Management	Consultant & researcher
4	Director	16	PhD	Construction Management	Owner research
5	Ass. Professor	10	PhD	Civil engineering	
6	Lecturer	6	Master’s degree	Construction management	Owner research
7	Civil engineer	7	Master’s degree	Civil engineering	Client
8	Senior BIM manager	>20	Master’s degree	Architecture	Consultant
9	Senior BIM manager	>20	Master’s degree	BIM and mechanical engineering	Owner
10	Civil Engineer	5	Master’s degree	Civil engineering	Owner
11	Civil Engineer	7	Master’s degree	Civil engineering	Owner

selected experts were requested to provide feedback on the AHP survey, describing the goal, criteria, alternatives, and procedures to be followed during their judgments. Table 2 provides the profiles of the 11 experts who were responsive and agreed to participate in this study, highlighting their key demographic and professional characteristics.

- Step 4: Building pairwise comparison matrices with fuzzy scales

Based on the hierarchical structure developed in Table 1, the AHP questionnaire was formulated and sent to experts to compare the level of importance of criteria, strategic decisions, and alternatives. The matrix is based on a hierarchy with n criteria or factors so that each expert is expected to make a total of n (n-1)/2 pairwise comparisons in each of the three levels of the hierarchy [67,73,74].

- Step 5: Establishing Comparison Matrices

As explained in Mahad et al [75], the comparison matrix for each expert indicated in Equation (1) & Equation (2) are established.

$$\breve{A} = \begin{bmatrix} 1 & a_{12} & \cdots & a_{1n} \\ a_{21} & 1 & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & 1 \end{bmatrix} \quad (1)$$

The matrix has reciprocal properties, which are:

$$a_{ij} = \frac{1}{a_{ij}}, \forall i, j = 1, 2, 3....n \quad (2)$$

where,

$$\widetilde{a}_{ij} = \left\{ \begin{array}{l} \widetilde{1}, \widetilde{2}, \widetilde{3}, \widetilde{4}, \widetilde{5}, \widetilde{6}, \widetilde{7}, \widetilde{8}, \widetilde{9} \ \ Criterion\,i\,relative\ \ impor\tan ce\ \ to\ \ criterion\ \ j \\ 1, \forall i = j\ \ criterion\ \ i\ \ isequal\ \ impor\tan ce\ \ criterion\ \ j \\ \widetilde{1}^{-1}, \widetilde{2}^{-1}, \widetilde{3}^{-1}, \widetilde{4}^{-1}, \widetilde{5}^{-1}, \widetilde{6}^{-1}, \widetilde{7}^{-1}, \widetilde{8}^{-1}, \widetilde{9}^{-1} \ \ criterion\ \ i\ \ is\ \ relative\ \ impor\tan ce\ \ to\ \ criterion\ \ j \end{array} \right\}$$

The linguistic variables, obtained from experts, were transformed into a triangular fuzzy number based on Afolayan et al [76], as shown in Table 4. The pairwise comparison judgements are represented as a fuzzy triangular numbers represented by equations (6) and (7).

- Step 6: Computation of the Consistency Index and Ratio

After experts made their judgments, it is important to consider whether or not the data are consistent. Some degree of inconsistency in the experts' responses is expected and acceptable in AHP analysis. For the acceptable limit of inconsistency (0.1), Saaty's [71] model is used. To calculate the inconsistency ratio, the inconsistency index is computed using equation (3).

$$CI = \frac{\lambda_{\max} - n}{n - 1} \quad (3)$$

Where the $\lambda_{\max}$ is the largest Eigenvalue of the comparison matrix and n is the dimension of the matrix.

The consistency ratio (CR) is defined as a ratio between the consistency of a given evaluation matrix and the consistency of a random matrix Equation (4) and Table 3.

$$CR = \frac{CI}{RI} \quad (4)$$

Where RI is a random consistency index attained from a large number of simulations runs and varies depending on the number of criteria as shown in Table 3. If CR is greater than 0.1, the value indicates inconsistent judgment. In such a case, the expert is encouraged to reconsider and revise the original values in the pairwise comparisons [77].

- Step 7: Establishing Fuzzy Pairwise Comparison Matrices

Transform the comparison matrix expressed in Equation (1) to a fuzzy set based on Table 4 and employ Equation (5). Matrix A represents the fuzzy judgment matrix of the nth decision maker's preference for ith criterion, whereby the fuzzy transformation becomes one as indicated in Equation (5). Where, l_{ij}, m_{ij}, u_{ij} are the minimum possible, most likely, and the maximum possible value of a

Table 3
Random consistency index (RI).

n	1	2	3	4	5	6	7	8	9	10
RI	0	0	0.58	0.9	1.12	1.24	1.32	1.4	1.45	1.12

Table 4
Saaty's scale vs Fuzzy AHP [76].

Linguistic Variables	Sarty's Scale	Fuzzy AHP Scale	
	(Crisp AHP Scale)	TFN	Reciprocal TFS
Equally important	1	(1,1,1)	(1,1,1)
Equally to Moderately Important	2	(1,2,3)	(1/3,1/2,1)
Moderately Important	3	(2,3,4)	(1/4,1/3,1/2)
Moderately to Strongly Important	4	(3,4,5)	(1/5,1/4,1/3)
Strongly Important	5	(4,5,6)	(1/6,1/5,1/4)
Strongly to Very Strongly Important	6	(5,6,7)	(1/7,1/6,1/5)
Very Strongly Important	7	(6,7,8)	(1/8,1/7,1/6)
Very Strongly to Extremely Important	8	(7,8,9)	(1/9,1/8,1/7)
Extremely Important	9	(8,9,9)	(1/9,1/9,1/8)

fuzzy number via TFN respectively [76]; [67].

$$\breve{A} = \begin{bmatrix} 1 & (l_{12}, m_{12}, u_{12}) & \cdots & (l_{1n}, m_{1n}, u_{1n}) \\ \left(\frac{1}{u_{12}}, \frac{1}{m_{12}}, \frac{1}{l_{12}}\right) & 1 & \cdots & (l_{2n}, m_{2n}, u_{2n}) \\ \vdots & \vdots & \ddots & \vdots \\ \left(\frac{1}{u_{1n}}, \frac{1}{m_{1n}}, \frac{1}{l_{1n}}\right) & \left(\frac{1}{u_{2n}}, \frac{1}{m_{2n}}, \frac{1}{l_{2n}}\right) & \cdots & 1 \end{bmatrix} \tag{5}$$

$$\mu A\left(\tilde{a}_{ij}\right) : R \rightarrow [0-1] \text{ where } \mu_A\left(a_{ij}\right) \tag{6}$$

$$\mu_A\left(a_{ij}\right) = \left\{ \begin{array}{l} 0, \tilde{a}_{ij} < l \\ \tilde{a}_{ij} - l_{ij} / m_{ij} - l_{ij}, l_{ij} \leq \tilde{a}_{ij} \leq m_{ij} \\ n - \tilde{a}_{ij} / u_{ij} - m_{ij}, m_{ij} \leq \tilde{a}_{ij} \leq u_{ij} \\ 0 \quad \tilde{a}_{ij}\left(l_{ij} \text{ or } a_{ij}\right) u_{ij} \end{array} \right\} \tag{7}$$

- Step 8: Aggregate Experts' Judgement

In the aggregation of experts' decisions, the study used Buckley's [78] most widely used fuzzy geometric mean approach as formulated in Equation (8).

$$\tilde{r}_i = \left(\prod_{i=1}^{n} \left(\tilde{a}_{ij}\right) \right)^{\frac{1}{n}} \tag{8}$$

Where $\tilde{r}_i$ is the geometric mean of fuzzy comparison values.

- Step 9: Determine of the Fuzzy Priority Weights

The computation of the fuzzy weights of each criterion, strategic decision, and alternative defuzzification are used to transform the fuzzy numbers into crisp values. Equation (8) transforms the individual fuzzy numbers into non-fuzzy or crisp ones. Then, the matrix M_i is transformed to $F = [f_i]$, Where the element matrix for f_i is calculated using Equation (9). The sum of local weights of criteria, decisions, and alternatives on the same hierarchy should be one, and the same is tested in the present study.

$$f_i = \frac{M_i}{\sum_{i=1}^{n} M_i} \tag{9}$$

- Step 10: Determination of Weights

At this stage, the components of weight vectors of the criteria are determined using Equation (10).

$$w_i = \frac{f_i}{n} \quad \forall_i \in \{1, 2, \ldots, n\} \tag{10}$$

3.3. Data description

In an Analytic Hierarchy Process (AHP) problem, it is very important to clearly define the hierarchy and decision criteria based on the description of the problem. The goal of the decision is identified and described. This goal should then be broken down into a hierarchical structure consisting of criteria, strategic decisions and alternatives that contribute to achieving the overall goal. To ensure clarity and consistency within the decision context, each criterion and strategic decision is described in detail in preceding section.

Based on the problem definition, a carefully crafted AHP questionnaire was developed, reviewed by experienced experts, and finalized after incorporating the feedback. The final questionnaire was distributed to specifically selected experts to obtain their professional opinion on the problem. Out of the 20 experts invited, 11 responded positively and voluntarily participated throughout the entire process.

Experts with proven experience in built asset management, building maintenance management, asset ownership, building information modelling, property management, and research were recruited for the study. The experts received a link to complete the AHP questionnaire in Google Sheets. Summary of the characteristics of participating experts is presented in Table 2.

3.4. Study validity and reliability measures

Validity and reliability tests are important to assess study quality. The validity and reliability tests were carried out to measure the quality of the present study.

Validity: The measures used in this study were selected based on existing research on similar topics, ensuring the validity of their content. In addition, the AHP questionnaire tool was reviewed by a panel of three experts with extensive academic and practical experience. Their valuable insights and suggestions were incorporated into the necessary revisions to improve the quality of the AHP questionnaire. To assess ease of use and estimate completion time, a pilot survey was conducted to evaluate the simplicity and comprehensibility of the survey instrument.

Reliability Test: To assess the reliability of collected data, consistency checks were performed using a consistency ratio to be less than 0.1.

4. Results

This section provides results of the fuzzy-AHP analysis, following the steps described in the study design section. The results for each set of criteria, strategic decisions, and alternatives are presented in tables followed by a concise description to facilitate understanding and interpretation. The aggregated defuzzified values of the criteria judgments, as derived from 11 experts, are presented in Table 5. In accordance with the steps outlined in the study design section. The normalized comparison weight matrix and the priority vector aggregate for all experts with respect to the goal is presented in Table 6.

As illustrated in Table 6, the cost criterion ranked highest, with a weight value of 0.515, signifying its predominant influence in determining the information requirements for the three operational phase strategic decisions. In the context of optimizing asset performance within the value model, the aim is to balance cost, risk, and business value. The risk and business value criteria, with weights of 0.252 and 0.231 respectively, reflect their comparable significance, underscoring their equal importance in this decision-making process. The pairwise comparison of aggregate from all experts for the three strategic decisions of cost, risk, and business value criteria are presented in Table 7, Table 8 and Table 9.

Table 10 through 12 present the normalized weights and priority vectors for each of the three strategic decisions, as evaluated against the criteria of cost, risk, and business value. These tables provide a detailed comparison of how each decision aligns with the specified evaluation criteria, offering insights into the relative importance and prioritization of each factor in the decision-making process.

The result shown in Table 10 illustrates that the cost criterion takes first place as a decision criterion. The result explains the decision to improve/adapt a bult asset shall be first determined by the cost criterion.

Table 11 shows that the risk criterion is the most significant factor in the decision to disassemble, taking precedence over the other two criteria, namely cost and business value. This indicates that risk plays a primary role in guiding the decision-making process in this context.

The results in Table 12 demonstrate that the business value criterion emerges as the foremost factor/criterion in decision-making. This finding suggests that decisions regarding improving or adapting buildings should be primarily guided by business value, rather than by cost or risk criteria considerations.

Information requirements are also evaluated as alternatives to be prioritized for each strategic decision. The opinions obtained from experts were analysed, and results are presented in Table 13 to Table 15. The result shows the aggregated pairwise comparison matrix

Table 5
Pairwise comparison for criteria with respect to goal.

Criteria	Cost (1)	Risk (2)	Business value (3)
Cost (1)	1.000	2.249	2.034
Risk (2)	0.445	1.000	1.204
Business value (3)	0.492	0.831	1.000

Table 6
Normalized weights and priority vectors of criteria.

Criteria	Cost (1)	Risk (2)	Business value (3)	Sum	Criteria Weights	Rank
Cost (1)	0.5165	0.5513	0.4800	1.5477	0.5159	1
Risk (2)	0.2296	0.2451	0.2840	0.7588	0.2529	2
Business value (3)	0.2539	0.2036	0.2360	0.6935	0.2312	3

Table 7
Pairwise comparison of strategic decisions with respect to cost.

Strategic decisions	Maintain (1)	Improve (2)	Deconstruct (3)
Maintain (1)	1.000	0.207	3.527
Improve (2)	4.831	1.000	7.091
Deconstruct (3)	0.287	0.141	1.000

Table 8
Pairwise comparison matrix of decisions with respect to risk.

Strategic decisions	Maintain (1)	Improve (2)	Deconstruct (3)
Maintain (1)	1.000	3.425	0.457
Improve (2)	0.292	1.000	0.252
Deconstruct (3)	2.190	3.964	1.000

Table 9
Pairwise comparison matrix of decisions with respect to business value.

Strategic decisions	Maintain (1)	Improve (2)	Deconstruct (3)
Maintain (1)	1.000	0.221	3.147
Improve (2)	4.529	1.000	6.298
Deconstruct (3)	0.318	0.159	1.000

Table 10
Normalized weights & priority vectors of decisions with respect to cost.

Strategic decisions	Maintain (1)	Improve (2)	Deconstruct(3)	Sum	Criteria weights	rank
Maintain (1)	0.164	0.154	0.304	0.621	0.207	2
Improve (2)	0.790	0.742	0.610	2.142	0.714	1
Deconstruct (3)	0.047	0.105	0.086	0.238	0.079	3

λmax = 3.09 and CR = 0.078.

Table 11
Normalized weights & priority vectors of decisions with respect to risk.

Strategic decisions	Maintain (1)	Improve (2)	Deconstruct (3)	Sum	Criteria Weights	Rank
Maintain (1)	0.287	0.408	0.267	0.963	0.321	2
Improve (2)	0.084	0.119	0.148	0.351	0.117	3
Deconstruct (3)	0.629	0.473	0.585	1.687	0.562	1

λmax = 3.05 and CR = 0.039.

Table 12
Normalized weights & priority vectors of decisions with respect to business value.

Strategic decisions	Maintain (1)	Improve (2)	Deconstruct (3)	Sum	Criteria Weights	Rank
Maintain (1)	0.171	0.160	0.301	0.632	0.211	2
Improve (2)	0.775	0.725	0.603	2.102	0.701	1
Deconstruct (3)	0.054	0.115	0.096	0.265	0.088	3

λmax = 3.08 and CR = 0.065.

Table 13
Information requirement with respect to maintain decision.

Information requirements	Technical (T)	Managerial (M)	Financial (F)	Legal (L)	Commercial (C)
Technical (T)	1.000	0.199	0.200	0.220	0.271
Managerial (M)	5.027	1.000	2.691	2.409	2.438
Financial (F)	5.010	0.372	1.000	0.561	0.382
Legal (L)	4.547	0.415	1.782	1.000	1.000
Commercial (C)	3.690	0.410	1.878	1.000	1.000

for the 11 experts, listing the categories of information requirements in relation to each strategic decision. For instance, pairwise comparison results aggregated value of experts for information requirements concerning maintain decision, improve and deconstruct decisions are shown in Table 13, Table 14 and Table 15 respectively.

The normalized pairwise comparison matrix obtained from experts for information requirements with respect to each strategic decision was calculated. Table 16 to Table 18 show the normalized weights and priority vectors of the information requirements about strategic decisions. For instance, experts aggregated normalized comparative weight matrix for information requirements concerning improve/adapt decisions is shown in Table 16.

Following the analysis conducted in the preceding sections, the specific information requirements pertinent to each strategic decision for operational team based on predefined criteria are evaluated. The findings reveal that notable variations in the information requirements across different strategic decisions, encompassing differences in type, level of detail, and composition within each decision. Fig. 4 illustrates the finalized composition of these information requirements framework, while detailed descriptions for each strategic decision are provided in the discussion subsequent section.

5. Discussion

Based on the results presented in preceding section, the information requirements and their composition to each strategic decision are discussed in the subsequent sections.

5.1. Information requirement for maintain/keep decision (1)

To make informed maintain/keep decisions, the information requirement from the five categories of information is prioritized for BIM-enabled AIM for public buildings in the study context. Accordingly, the result revealed that technical information is less important than others, as shown in Fig. 4. As illustrated in Table 17, managerial information is identified as the highest priority category for buildings with regard to maintain/keep decisions. This finding underscores the critical role that access to and utilization of managerial information plays in effectively guiding and sustaining these decisions, highlighting its importance above other potential considerations. This further indicates the importance of asset condition data, maintenance schedule and history, asset type, and category in this strategic decision. Financial information has relatively the lowest priority among other categories, suggesting that financial considerations are less important. The need for legal information remains a high priority, as compliance with legal requirements also plays a crucial role in implementing maintenance measures. Commercial information requirement is categorized as moderate level, indicating that market dynamics continue to play a role in maintaining buildings for business operations.

5.2. Information requirement for improve/adapt decision (2)

The priority vector of the AHP for technical information requirements in the context of improving/adapting decisions indicates a high level of importance for BIM-enabled AIM for public buildings in the study context. This suggests that graphical and attribute information related to design limits, parameters, and technical specifications is critically important in such strategic decisions. As explained, managerial information requirements are essential for improving/adapting strategic decisions. This is mainly because effective asset condition data, warranty information, work plans, and maintenance-related considerations play a significant role in decision-making. Financial information is relatively important but ranked behind technical, managerial, and legal information requirements, which indicates that financial considerations are not at the forefront of this strategic decision.

Legal information is considered moderately important, suggesting legal compliance plays a greater role in improvement decisions than financial information. Commercial information is regarded as least important, suggesting that the influence of data on the

Table 14
Information requirement with respect to improve/adapt decision.

Information requirements	Technical (T)	Managerial (M)	Financial (F)	Legal (L)	Commercial (C)
Technical (T)	1.000	1.659	2.652	3.202	3.782
Managerial (M)	0.603	1.000	1.312	1.462	2.884
Financial (F)	0.377	0.762	1.000	0.749	1.000
Legal (L)	0.312	0.684	1.335	1.000	1.817
Commercial (C)	0.264	0.347	1.000	0.550	1.000

Table 15
Information requirement with respect to deconstruct decision.

Information requirements	Technical (T)	Managerial (M)	Financial (F)	Legal (L)	Commercial (C)
Technical (T)	1.000	4.441	8.225	5.487	5.765
Managerial (M)	0.225	1.000	4.348	0.347	0.428
Financial (F)	0.122	0.230	1.000	0.232	0.446
Legal (L)	0.182	2.884	4.303	1.000	1.000
Commercial (C)	0.173	2.338	1.673	1.000	1.000

Table 16
Normalized weights and priority vectors for requirements with respect to maintain decision.

Information requirements	Technical (T)	Managerial (M)	Financial (F)	Legal (L)	Commercial (C)	Sum	Criteria weights	Rank
Technical	0.052	0.083	0.026	0.042	0.053	0.257	0.051	5
Managerial	0.261	0.417	0.356	0.464	0.479	1.978	0.396	1
Financial	0.26	0.155	0.132	0.108	0.075	0.731	0.146	4
Legal	0.236	0.173	0.236	0.193	0.196	1.034	0.207	2
Commercial	0.191	0.171	0.249	0.193	0.196	1	0.200	3

λmax = 5.06 and CR = 0.014.

Table 17
Normalized weights and priority vectors for requirements with respect to improve/adapt decision.

Information requirements	Technical	Managerial	Financial	Legal	Commercial	Sum	Criteria Weights	Rank
Technical	0.391	0.373	0.363	0.46	0.361	1.948	0.390	1
Managerial	0.236	0.225	0.18	0.21	0.275	1.125	0.225	2
Financial	0.147	0.171	0.137	0.108	0.095	0.659	0.132	4
Legal	0.122	0.154	0.183	0.144	0.173	0.776	0.155	3
Commercial	0.103	0.078	0.137	0.079	0.095	0.493	0.099	5

λmax = 5.12 and CR = 0.03.

Table 18
Normalized weights and priority vectors for requirements with respect to deconstruct decision.

Information requirements	Technical	Managerial	Financial	Legal	Commercial	Sum	Criteria Weights	Rank
Technical	0.587	0.408	0.421	0.68	0.667	2.763	0.553	1
Managerial	0.132	0.092	0.222	0.043	0.05	0.539	0.108	4
Financial	0.071	0.021	0.051	0.029	0.052	0.224	0.045	5
Legal	0.107	0.265	0.22	0.124	0.116	0.832	0.166	2
Commercial	0.102	0.215	0.086	0.124	0.116	0.642	0.128	3

λmax = 5.34and CR = 0.08.

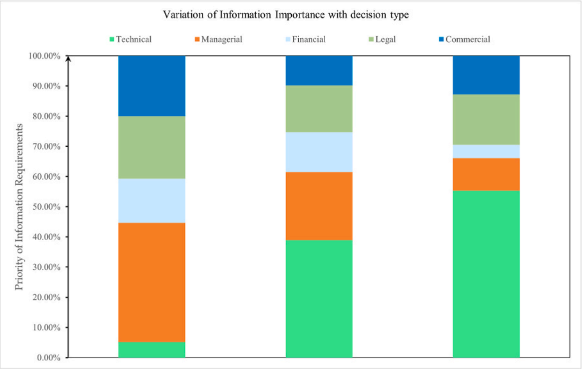

Fig. 4. Framework of information requirement for strategic decisions.

strategic decision to improve a building is relatively low.

5.3. Information requirement for deconstruct/disassemble decision (3)

The FAHP analysis revealed that technical information requirement is the most important category of information for deconstruct decision as shown in Table 18 for BIM-enabled AIM for public buildings in the study context. This is because technical information related to design parameters, design limits, and material specifications is vital for the decision on deconstruction. The goal of deconstruction is not just to replace a site but to efficiently reuse materials for an environmentally conscious decision. In this regard, technical information plays a crucial role in ensuring the safe modelling of deconstruction processes.

Managerial information requirements for this strategic maintenance decision have demonstrated a moderate level of importance, indicating that management aspects still hold some level of relevance in the process of deconstruction. Financial information exhibits a relatively lower priority, indicating that financial considerations have less weight in deconstructing decisions.

Legal information is ranked as the second highest priority for BIM-based Asset Information modelling for public buildings in the study context, which is a good reflection of the fact that legal compliance is a significant consideration in asset replacement strategic decisions. Commercial information is ranked lowest, suggesting that it exerts the least influence on the decision to deconstruct existing building.

6. Conclusion and recommendation

6.1. Conclusion

The performance of decision-making in public building management is strongly influenced by the quality of information, logistics, and data pertaining to a particular asset. The present study utilized the Fuzzy Analytic Hierarchy Process (FAHP) to prioritize information requirements for BIM-enabled AIM, specifically tailored to strategic decisions within public buildings. A framework of information requirements for BIM-enabled built asset management is developed in order to efficiently support strategic decisions in existing buildings.

Accordingly, the fuzzy-AHP analysis demonstrated that the information requirements significantly vary depending on the strategic decisions. For maintain decisions, the prioritization is mainly managerial (39.6 %), followed by legal (20.7 %) and commercial (20 %) information requirements. For improv/adapt, the priorities shift to technical aspects (39 %), followed by financial (15.5 %) and legal (13.5 %) information. In the case of decisions on deconstruct/disassemble, technical requirements (55.5 %) are strongly prioritized, followed by legal (16.6 %) and commercial (12.8 %).

The analysis reveals that the importance of different requirement of information technical, managerial, financial, legal, and commercial varies significantly depending on the type of strategic decision, emphasizing the need for purpose-driven data acquisition for efficient AIM.

While these insights offer valuable guidance for optimizing resource allocation and developing strategies that are more informed and context-specific, it is important to note the study's limitation. Given the small sample size and the specific context of the expert opinions surveyed, the generalizability of the findings may be limited. Therefore, while the study provides a strong foundation for understanding the importance of criteria-based information delivery in BIM-enabled AIM for existing building a resource environment. Further research is required to focus on testing these findings across diverse scenarios in broader samples to validate and refine the proposed framework of information requirements for better generalizability.

6.2. Recommendation

The results of the present study are based on a relatively small pool of experts, which may restrict the generalizability of the findings. To address this gap, it is recommended that future research endeavours expand the pool of experts consulted. By incorporating a more diverse and larger group of experts, the applicability and robustness of the results can be significantly improved, thereby providing a more comprehensive understanding of the subject matter.

6.3. Contribution to the literature

This study contributes to the existing state of knowledge by demonstrating the importance of a criteria-based information delivery process for efficient BIM-based asset information modelling in the digitization of existing buildings in transforming practices into a data-driven decision-making.

Limitation of the study

The results of this study are based on small pool of expert opinion in a specific scenario, which may affect replication for similar situations.

CRediT authorship contribution statement

Muluken Tilahun Desbalo: Writing – original draft, Validation, Resources, Methodology, Formal analysis, Data curation, Conceptualization. **Asregedew Kassa Woldesenbet:** Writing – review & editing, Validation, Supervision.

Consent to participate

Informed consent was obtained from all individual participants included in the study.

Consent to publish

The participant has consented to the submission of the article to the journal.

Ethical approval

The authors assert the alignment of this research involving human subjects with ethical principles and guidelines. While there are no direct human participants involved in this study, the data, consisting of opinions, gathered from an expert group is shared without exposing their personal information. All individual data is presented in an anonymized manner to uphold privacy and confidentiality.

Personal information

Personal information that is not essential for the research has been anonymized or removed. Any potentially identifying information in figures, tables, or images has been anonymized to protect the privacy of individuals.

Data availability

The primary and secondary data used to support this study's findings are available from the corresponding author.

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This study was not financially supported by any organization or institution.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: The submitted work (draft level) is available as a preprint online If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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