

## Article

# A BIM-Integrated Eco-Digital Framework for Markov-Based Predictive Maintenance and Sustainability Assessment in Educational Buildings Towards Digital Twin Readiness

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## Abstract

This study proposes a BIM-integrated Eco-Digital framework for enhancing predictive maintenance and sustainability assessment in educational buildings, supporting their transition towards Digital Twin readiness. Existing facilities often rely on reactive maintenance practices, fragmented data systems, and limited integration of sustainability indicators, which hinder efficient lifecycle management and environmental performance. To address these challenges, the research develops a data-driven methodology that combines condition assessment (CA), Markov-based deterioration prediction (DP), and sustainability metrics within an interoperable BIM–facility management (FM) environment. The framework is validated through a real educational building case study, where a hierarchical asset structure and relative weighting system are established to prioritize maintenance actions based on both functional importance and condition state. The Markov model is employed to predict component deterioration under uncertainty, enabling proactive maintenance planning without reliance on real-time IoT data. Sustainability is incorporated through energy consumption analysis and lifecycle performance indicators, linking maintenance decisions to environmental impacts. Results demonstrate improved maintenance prioritization, enhanced predictive capability, and better integration of sustainability considerations within facility management workflows. The proposed framework mainly contributes to providing a practical, scalable approach for transforming conventional buildings into data-driven, sustainable assets, offering a viable pathway toward Digital Twin-enabled environments, particularly in contexts with limited digital infrastructure.



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**Keywords:** Digital Twin readiness; predictive maintenance; BIM; sustainability assessment

## 1. Introduction

Educational buildings play a fundamental role in supporting learning environments, research activities, and institutional development. As long-term physical assets, their performance directly influences user comfort, productivity, and operational efficiency [1]. However, many existing educational facilities suffer from progressive deterioration due to aging infrastructure, limited maintenance budgets, and the absence of systematic facility management (FM) strategies [2]. Traditional maintenance practices in such buildings are often reactive, addressing failures only after they occur. This approach not only accelerates asset degradation but also leads to increased lifecycle costs, operational disruptions,

and reduced sustainability performance. Consequently, there is a growing need to shift toward more proactive and data-driven maintenance strategies that can enhance building performance while optimizing resource allocation [3].

In recent years, digital transformation in the built environment has introduced advanced tools such as Building Information Modeling (BIM) and Digital Twin (DT) technologies, offering new opportunities for improving facility management practices. BIM provides a structured platform for integrating geometric and non-geometric building data, while DT extends this capability by enabling dynamic, real-time interaction between physical assets and their digital representations. Despite these advancements, the implementation of predictive maintenance within BIM–FM workflows remains limited, particularly in existing educational buildings. Most current predictive approaches rely heavily on Internet of Things (IoT) sensors or machine learning techniques, which require extensive historical data and advanced infrastructure that are often unavailable in typical educational facilities. As a result, BIM models frequently remain static and disconnected from predictive decision-making processes, limiting their effectiveness in supporting long-term asset management [4,5].

Furthermore, existing frameworks rarely integrate condition assessment (CA), deterioration prediction (DP), facility management, and sustainability considerations within a single interoperable system [6]. Maintenance decision-making is often performed in isolation from sustainability metrics, such as energy consumption and lifecycle performance, preventing facility managers from evaluating the environmental implications of their actions [7,8]. This fragmentation creates a critical gap in achieving holistic, data-driven, and sustainable facility management [9]. In addition, the lack of practical, low-data predictive models further restricts the adoption of advanced maintenance strategies in resource-constrained environments [10]. These limitations highlight the need for an integrated framework that can support predictive maintenance and sustainability assessment without relying on real-time IoT data or complex machine learning models [11,12].

To address these challenges, this study aims to develop a BIM-integrated Eco-Digital framework that combines condition assessment, Markov-based deterioration prediction, and sustainability metrics within a unified facility management workflow. The framework is designed to support the transition of existing educational buildings toward Digital Twin readiness by enabling predictive, data-driven decision-making in environments with limited data availability. Specifically, the objectives of this research are to establish a hierarchical asset structure and relative weighting system to prioritize building components and spaces based on functional importance and condition state; to develop a Markov-based deterioration prediction model capable of forecasting component performance under uncertainty using limited inspection data; to integrate the predictive model within a BIM–FM environment to support maintenance planning, visualization, and decision-making; and to incorporate sustainability metrics, including energy performance and lifecycle considerations, to evaluate the environmental impact of maintenance strategies. Through these contributions, the study provides a practical and scalable approach for transforming conventional facility management practices into integrated, predictive, and sustainability-oriented systems, ultimately supporting the progression toward Digital Twin-enabled buildings.

## 2. Literature Review

### 2.1. Condition Assessment in Facility Management

Condition assessment (CA) is a fundamental component of facility management, providing the baseline information required to evaluate the physical state of building components and support maintenance decision-making [13]. It typically involves systematic inspection, rating, and analysis of building elements using standardized indices

such as the Facility Condition Index (FCI) [14]. Previous studies emphasize that effective CA enhances maintenance planning, improves resource allocation, and reduces lifecycle costs by enabling early identification of deterioration patterns [15]. However, conventional CA methods largely rely on manual inspections and visual assessments, which introduce subjectivity and inconsistency in data collection [16].

Despite its importance, CA is often implemented as a standalone process, disconnected from predictive modeling and digital systems [13]. This limits its ability to support proactive maintenance strategies. While recent advancements have explored automated inspection techniques using sensors and imaging technologies, their practical implementation remains limited in many existing buildings due to cost and infrastructure constraints [17]. As a result, there is a need to integrate CA within a broader, data-driven framework that enhances its role from descriptive evaluation to predictive decision support [13].

## 2.2. Deterioration Prediction Models

Deterioration prediction (DP) plays a critical role in forecasting the future performance of building components and enabling predictive maintenance strategies [18]. Existing approaches can be broadly categorized into deterministic, statistical, and artificial intelligence-based models [19]. Machine learning techniques have gained significant attention in recent years due to their ability to model complex patterns and large datasets [20]. However, these models typically require extensive historical data and continuous data streams, making them less suitable for buildings with limited data availability, such as educational facilities [20].

In contrast, statistical approaches, particularly the Markov chain, offer a more practical alternative for modeling deterioration under uncertainty [20]. Markov models represent component degradation as probabilistic transitions between discrete condition states, allowing predictions to be made using relatively sparse inspection data [21]. This makes them especially suitable for infrastructure systems where data is incomplete or irregular. Furthermore, Markov-based models provide transparency and interpretability, which are essential for decision-making in FM contexts [22].

## 2.3. BIM, Digital Twin, and Facility Management Integration

Building Information Modeling (BIM) has emerged as a key enabler of digital transformation in the architecture, engineering, and construction (AEC) industry [23]. By integrating geometric and semantic data within a unified digital model, BIM supports improved collaboration, visualization, and information management throughout the building lifecycle [24]. In the context of facility management, BIM has been extended to support operation and maintenance (O&M) activities, often referred to as 6D and 7D BIM [25]. However, BIM in its conventional form is largely static, lacking the capability to dynamically update and predict asset performance over time [26]. This limitation has driven the evolution toward Digital Twin (DT) concepts, which integrate real-time data, simulation, and predictive analytics to create a dynamic representation of physical assets [27]. DTs have demonstrated significant potential in enhancing predictive maintenance, energy management, and operational efficiency [28].

Despite these advancements, the integration of BIM, DT, and facility management remains fragmented [26]. Many existing implementations focus on isolated applications, such as energy monitoring or equipment tracking, without providing a comprehensive framework that links condition assessment, deterioration prediction, and maintenance execution [27]. Moreover, most DT applications rely heavily on IoT-enabled data streams, which are often unavailable in existing buildings [29]. This creates a gap between theoretical DT capabilities and practical implementation in resource-constrained environments,

highlighting the need for alternative approaches that can support DT readiness without full reliance on real-time data [30,31].

#### 2.4. Sustainability Metrics in Building Maintenance

Sustainability has become a critical consideration in the management of building assets, particularly during the operation and maintenance phase, which accounts for a significant portion of a building's lifecycle energy consumption and environmental impact [32]. Traditional maintenance strategies often overlook the relationship between component deterioration and sustainability performance, focusing primarily on cost and functionality [33]. Recent studies emphasize the importance of integrating sustainability metrics such as energy consumption, lifecycle cost, and component durability into FM practices [34]. These metrics enable a more holistic evaluation of building performance by linking maintenance decisions to environmental outcomes [35]. For example, inefficient or deteriorated components can lead to increased energy consumption and reduced operational efficiency, while timely maintenance can extend service life and reduce environmental impact [36].

However, the integration of sustainability metrics into predictive maintenance frameworks remains limited [19]. Existing BIM-FM workflows often lack mechanisms to quantify the environmental implications of maintenance decisions, resulting in fragmented and incomplete sustainability assessments [20]. This gap highlights the need for frameworks that combine predictive maintenance with sustainability evaluation to support more informed and environmentally responsible decision-making [37,38].

#### 2.5. Research Gap

Although significant progress has been made in the fields of CA, deterioration modeling, BIM integration, and sustainability evaluation, these components are often addressed independently in the literature [19,20]. There is a clear lack of integrated frameworks that combine CA, DP, BIM, FM, and sustainability metrics within a unified system. Furthermore, existing predictive maintenance approaches are frequently dependent on data-intensive methods, such as machine learning and IoT-based monitoring, limiting their applicability in environments with limited data infrastructure [26].

In addition, the potential of Markov-based deterioration models as a data-efficient and transparent alternative has not been fully explored within BIM-integrated workflows [20]. Similarly, sustainability considerations are rarely embedded within predictive maintenance models, preventing a comprehensive assessment of both operational and environmental performance. Therefore, there is a critical need for a practical, interoperable, and data-efficient framework that integrates all these aspects to support predictive maintenance and enable the transition of existing buildings toward Digital Twin readiness [23]. Unlike previous BIM-FM studies that primarily focus on information management and visualization, the proposed framework integrates condition assessment, relative weighting, Markov-based deterioration prediction, facility management workflows, and sustainability metrics within a unified environment. Furthermore, while many Digital Twin readiness frameworks depend on real-time IoT data streams and advanced sensing infrastructure, the proposed approach enables predictive maintenance using periodic inspection data, making it applicable to existing educational buildings with limited digital infrastructure. In contrast to conventional Markov deterioration models that operate as standalone analytical tools, the developed framework embeds deterioration forecasting directly within a BIM-FM environment, allowing maintenance prioritization, visualization, and sustainability assessment to be performed simultaneously. These characteristics distinguish the proposed framework from existing approaches and provide a practical pathway toward Digital Twin

readiness. Table 1 presents a comparison of the proposed framework with existing BIM-FM, DT-readiness, and predictive maintenance studies.

**Table 1.** Comparison of the proposed framework with existing BIM-FM, DT-readiness, and predictive maintenance studies.

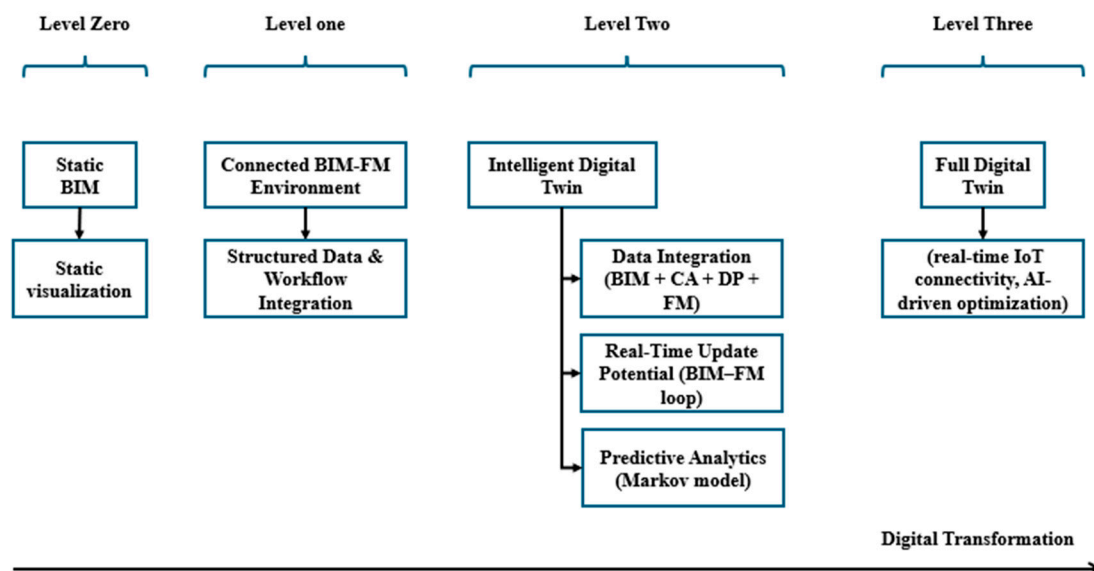
| Study               | BIM-FM Integration | Deterioration Prediction | Sustainability Metrics | DT Readiness | IoT Dependency |
|---------------------|--------------------|--------------------------|------------------------|--------------|----------------|
| Gerber et al. [25]  | ✓                  | x                        | x                      | x            | x              |
| Boje et al. [26]    | ✓                  | x                        | x                      | ✓            | ✓              |
| Opoku et al. [27]   | ✓                  | Limited                  | x                      | ✓            | ✓              |
| Zhang et al. [20]   | x                  | ✓ (Markov)               | x                      | x            | x              |
| Arayici et al. [34] | ✓                  | x                        | ✓                      | Limited      | x              |
| Proposed Framework  | ✓                  | ✓ (Markov)               | ✓                      | ✓            | x              |

✓ the study included this aspect, x the study excluded this aspect.

### 3. Methodology

#### 3.1. Research Framework Overview

This study adopts a mixed-methods approach that integrates quantitative modeling with qualitative data collection to develop a BIM-based predictive maintenance framework. The proposed methodology is structured around an Eco-Digital framework, which combines CA, DP, sustainability evaluation, and FM within a unified workflow. The framework is designed to support data-driven decision-making and enable the transition of existing buildings toward Digital Twin readiness without reliance on real-time Internet of Things (IoT) data, as shown in Figure 1.



**Figure 1.** Digital Twin capability level transformation.

The methodological workflow consists of four main stages: condition assessment and data collection, development of a relative weighting system, Markov-based deterioration prediction modeling, and integration within a BIM-FM environment with embedded sustainability metrics. This structured approach ensures both analytical rigor and practical applicability in real-world facility management contexts.

### 3.2. Condition Assessment (CA)

The first stage of the methodology involves evaluating the physical condition of building components through a structured CA process. A hierarchical asset structure is established to organize building elements into multiple levels, including building, space, category, sub-category, and component. This hierarchy ensures consistent data collection and facilitates detailed performance evaluation across different building systems.

A direct condition rating method is employed, where each component is assigned a score on a standardized scale (e.g., 0–100) based on its observed physical condition [14]. Data collection is conducted through field inspections. Due to the absence of IoT infrastructure, manual inspection is adopted as the primary data source, representing a realistic scenario for many existing educational buildings. The resulting condition indices serve as the baseline input for subsequent modeling and analysis.

### 3.3. Relative Weighting (RW) System

To enhance maintenance prioritization, a relative weighting (RW) system is developed to quantify the importance of different building spaces and components. The RW model integrates user perception and spatial characteristics by combining physical attributes such as space area and usage frequency.

A field inspection was conducted by building users, including students, academic staff, and administrative personnel, to evaluate the functional importance of different spaces (e.g., classrooms, laboratories, offices). A total of 85 individuals were invited to participate in field inspection of the building (11 faculty members, 23 teaching assistants, and 51 students), of which 72 completed the assessment, resulting in a response rate of 84.7%. The responses are analyzed using a Likert-scale approach to calculate relative importance scores [35]. These scores are then adjusted based on spatial parameters to produce a final RW for each space and its associated components. This weighting mechanism ensures that maintenance decisions are not based solely on physical condition but also consider functional criticality, enabling a more balanced and user-centered prioritization strategy.

To improve reliability and reduce individual bias, the field inspection incorporated a diverse group of stakeholders representing different building users. This diversity enhances the representativeness of the collected data and aligns with participatory facility management approaches, where multiple stakeholders contribute to performance evaluation and maintenance prioritization [9]. Furthermore, the relative weights derived from stakeholder assessments were not used independently but were integrated within a structured hierarchical framework that also considers spatial characteristics and condition assessment results.

### 3.4. Deterioration Prediction Model

To forecast the future condition of building components, a probabilistic deterioration prediction model is developed using the Markov chain approach [18]. This method models component degradation as transitions between discrete condition states over time, capturing the inherent uncertainty and variability in deterioration processes. The model is calibrated using CA data, where transition probabilities are derived based on observed condition changes and estimated service life. A discrete-time framework is adopted, allowing predictions to be generated at defined time intervals (e.g., annually) [20].

The Markov model is selected due to its ability to operate effectively with limited data, making it suitable for buildings where historical maintenance records and real-time monitoring are unavailable. The output of the model includes predicted condition states and deterioration rates for building components, which are subsequently used to inform maintenance planning and prioritization.

The deterioration process is governed by a transition probability matrix  $P_{ij}$ , which represents the probability of a component moving from condition state  $i$  to condition state  $j$  during a fixed time interval. The transition matrix satisfies the following Markov properties, where the sum of transition probabilities in each row equals one, ensuring that all possible future states are accounted for.

The model was calibrated using condition assessment data collected during the field inspection process. Transition probabilities were estimated based on observed deterioration patterns, expected service life information, and engineering judgment derived from facility management records. Since the model assumes a pure deterioration scenario without maintenance intervention, transitions to improved condition states were not permitted. An initial condition distribution vector,  $v$ , was established from the current observed condition states of building components. The future condition distribution after  $n$  time intervals was then calculated as follows:

State Definitions: Discrete condition states  $S = \{1, 2, \dots, n\}$ .

Transition Matrix  $P_{ij}$ : Probabilities of moving from state  $ii$  to  $jj$  in a fixed interval.

Key Properties:  $P_{ij} \geq 0$  and  $\sum_j P_{ij} = 1$  (probabilities sum to 1). The initial distribution  $v$  evolves over  $n$  steps as  $vP^n$ . The Markov model was selected due to its ability to operate effectively with limited inspection data, making it particularly suitable for educational buildings where extensive historical records and real-time IoT monitoring are unavailable.

### 3.5. BIM–FM Integration

The developed predictive model is integrated within a BIM-based FM environment to enable visualization, automation, and decision support. The BIM model is created using Autodesk Revit, incorporating data related to building components. Data interoperability is achieved through the use of Construction Operations Building Information Exchange (COBie) standards, allowing seamless data transfer between the BIM model and FM systems [25].

The integrated workflow connects predicted deterioration outputs with maintenance management processes, enabling the generation of preventive maintenance plans and work orders. This integration enhances the ability of facility managers to visualize component conditions, track performance over time, and make informed maintenance decisions within a centralized digital platform.

### 3.6. Sustainability Integration

To incorporate environmental considerations into maintenance decision-making, sustainability metrics are embedded within the framework. These metrics focus primarily on energy consumption and lifecycle performance, linking component deterioration to operational efficiency and environmental impact [32].

Energy consumption data is analyzed to assess the relationship between component condition and building performance. The integration of sustainability indicators enables the evaluation of maintenance strategies not only in terms of cost and functionality but also in terms of their ecological implications. This approach supports a more holistic understanding of building performance and aligns maintenance practices with sustainability objectives.

### 3.7. Case Study Application

The proposed methodology is validated through its application to a real educational building at the British University in Egypt. The case study provides a practical context for implementing the framework, including data collection, model calibration, and system

integration. Building spaces such as classrooms, computer laboratories, and offices are analyzed to demonstrate the effectiveness of the approach in prioritizing maintenance and predicting deterioration. The results of the case study are used to evaluate the performance of the framework in terms of predictive capability, maintenance optimization, and sustainability assessment, ensuring both theoretical and practical validation of the proposed methodology.

## 4. Model Development and Case Study

### 4.1. Case Study Overview

The proposed framework is validated through its application to a real educational facility. The selected building represents a typical university academic facility composed of multiple functional spaces, including classrooms, computer laboratories, administrative offices, and teaching assistant offices as shown in Figure 2, where Table 2 summarizes space types with the corresponding numbers and area. As with many existing educational buildings, the facility operates under conventional maintenance practices characterized by reactive interventions, limited data integration, and the absence of predictive decision support tools.

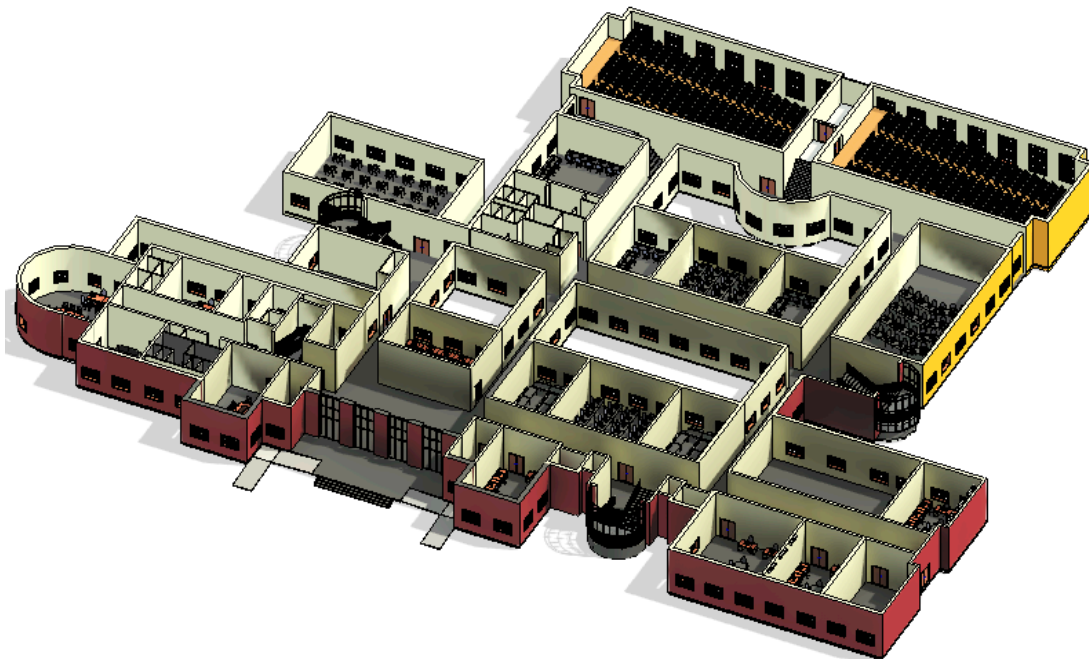


Figure 2. 3D model of building A, ground floor plan, BUE.

Table 2. Type of spaces on the ground floor with the corresponding numbers and area.

| # | Type             | Space Numbers | Area m <sup>2</sup> |
|---|------------------|---------------|---------------------|
| 1 | Classroom        | 2             | 95                  |
| 2 | Exam Office      | 1             | 122                 |
| 3 | IT Office        | 2             | 64                  |
| 4 | Meeting Room     | 1             | 33                  |
| 5 | Bathroom         | 2             | 79                  |
| 6 | Buffet           | 1             | 15                  |
| 7 | Computer Lab     | 7             | 411                 |
| 8 | Corridor/lobbies | -             | 811                 |

Table 2. Cont.

| #     | Type                                   | Space Numbers | Area m <sup>2</sup> |
|-------|----------------------------------------|---------------|---------------------|
| 9     | Printing room                          | 1             | 5.5                 |
| 10    | Drawing Room                           | 1             | 124.5               |
| 11    | Lecture Hall                           | 2             | 513                 |
| 12    | Office (TA, Administrative, Dr, Deans) | 11            | 499                 |
| Total |                                        |               |                     |
| Total |                                        | 31            | 2772                |

The case study was selected to reflect common challenges in educational environments, including aging infrastructure, diverse component types, and constrained maintenance resources. These characteristics make it an appropriate testbed for evaluating the applicability and effectiveness of the proposed Eco-Digital framework in real-world conditions.

#### 4.2. Asset Classification and Modeling

To support systematic analysis, the building was structured using a hierarchical asset classification approach. The hierarchy organizes the facility into multiple levels, including building, space, category, sub-category, and component. This structure enables consistent evaluation of elements across different disciplines, such as architectural, mechanical, and electrical systems, as shown in Figure 3.

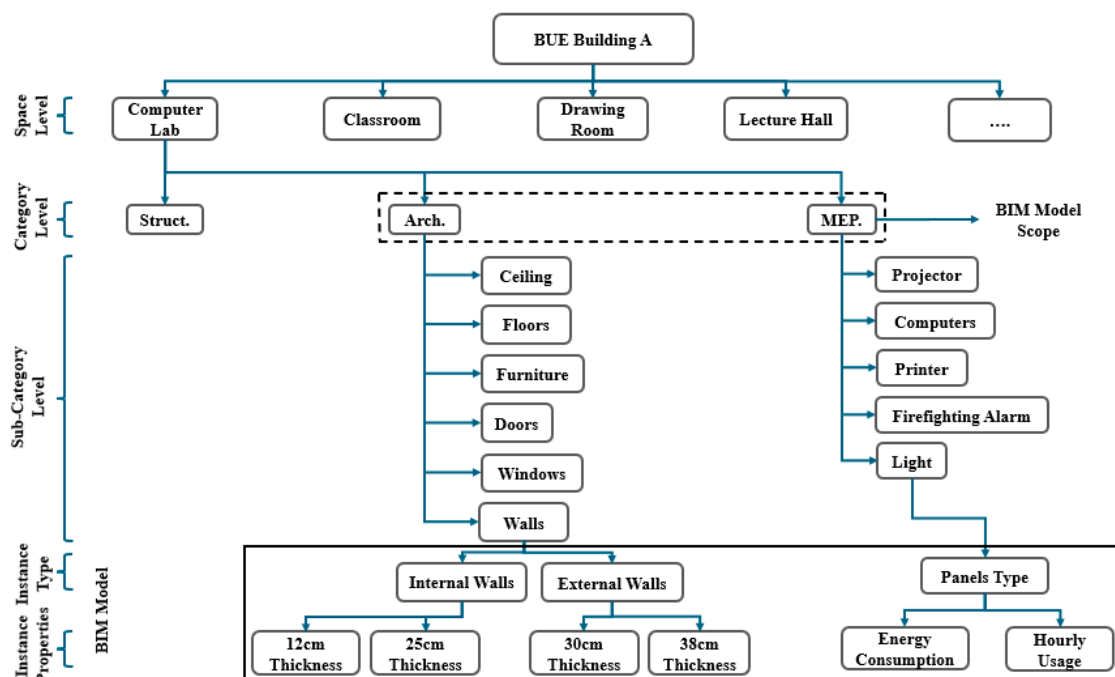


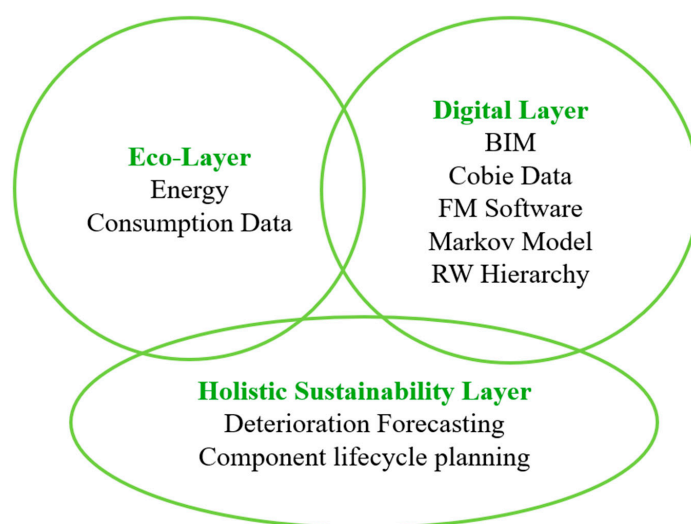
Figure 3. Building asset hierarchy.

The collected data were mapped onto this hierarchical structure to facilitate CA, weighting calculations, and deterioration modeling. Each space type (e.g., classrooms, laboratories, offices) was analyzed individually to capture variations in usage, importance, and performance requirements. This classification also supports the integration of data within the BIM environment, ensuring compatibility with facility management workflows.

#### 4.3. Implementation of the Proposed Framework

The case study served as a platform for implementing the full methodology of the proposed framework. First, CA results and RW were combined to establish a prioritized understanding of building performance. Next, the Markov chain model was applied to predict the future condition states of building components over defined time intervals. The predictive outputs were then integrated into a BIM-based environment developed using Autodesk Revit, with data exchange facilitated through COBie standards. This integration enabled the visualization of component conditions, linking predicted deterioration states with maintenance management processes.

A facility management (FM) system was utilized to generate maintenance plans and work orders based on the predicted deterioration and prioritization results. As shown in Figure 4, the proposed framework combines the Eco-Layer (energy consumption data) and the Digital Layer (BIM, COBie data, FM software, Markov model, and RW hierarchy) to establish a Holistic Sustainability Layer that supports deterioration forecasting and component lifecycle planning, ultimately facilitating the transformation toward a Digital Twin (DT)-enabled building.



**Figure 4.** Eco-Digital fusion and sustainability metrics for achieving the transformation to a DT-enabled building.

## 5. Results and Discussion

### 5.1. Condition Assessment and Relative Weighting Results

The condition assessment (CA) results revealed significant variation in the physical condition of building components across different space types. Spaces such as teaching assistant offices and computer laboratories exhibited relatively higher deterioration levels compared to standard classrooms and administrative areas. This variation reflects differences in usage intensity, occupancy patterns, and equipment dependency. The integration of the relative weighting (RW) system provided an additional layer of insight by incorporating functional importance into the evaluation process. Spaces with high operational significance, particularly computer laboratories, were assigned higher weights due to their critical role in academic activities.

Figure 5 presents the relative weights of spaces based on building users, while Figure 6 presents the adjusted relative weights (RW), illustrating the impact of these factors on space prioritization. The relative weights were further detailed by examining the surface area and the number of spaces. For instance, the relative weight of computer labs initially reported from the survey was 0.096 based on their 411 m<sup>2</sup> area, which constituted 14% of the total

area, subsequently increasing the weight to 0.161. Table 3 provides a summary of the RW for each category with respect to surface area, demonstrating variability across different types of spaces. The initial relative weight for each space type,  $RW(SQ)$ , was calculated using the mean value of stakeholder responses. Subsequently, area normalization was performed to account for the influence of space size on maintenance priority. The final RW of each space,  $RW(SP)$ , was calculated using

$$RW(SP) = [RW(SQ) \times \text{Area}(CS)] / \sum [RW(SQ) \times \text{Area}(CS)] \quad (1)$$

where

$RW(SQ)$  = RW derived from user assessments based on mean response values;

$\text{Area}(CS)$  = area of the corresponding space obtained from the case study;

$RW(SP)$  = final normalized relative weight of the space.

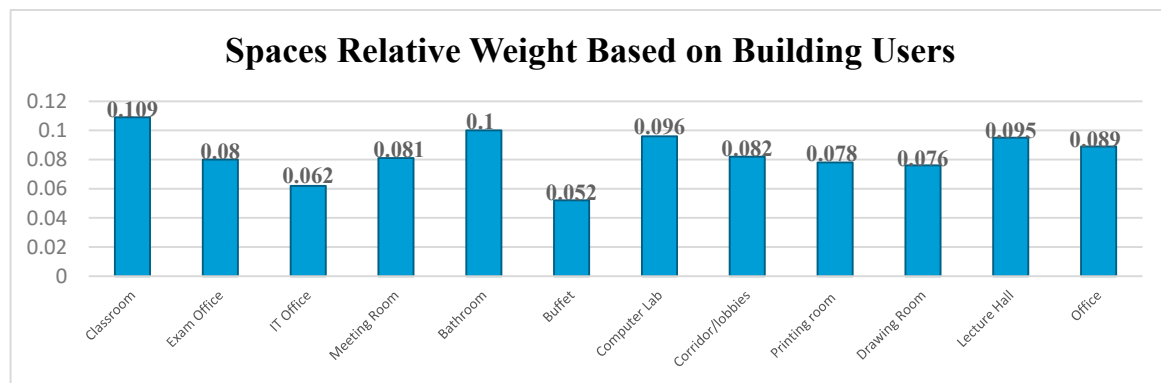


Figure 5. Relative weight of spaces based on building users.

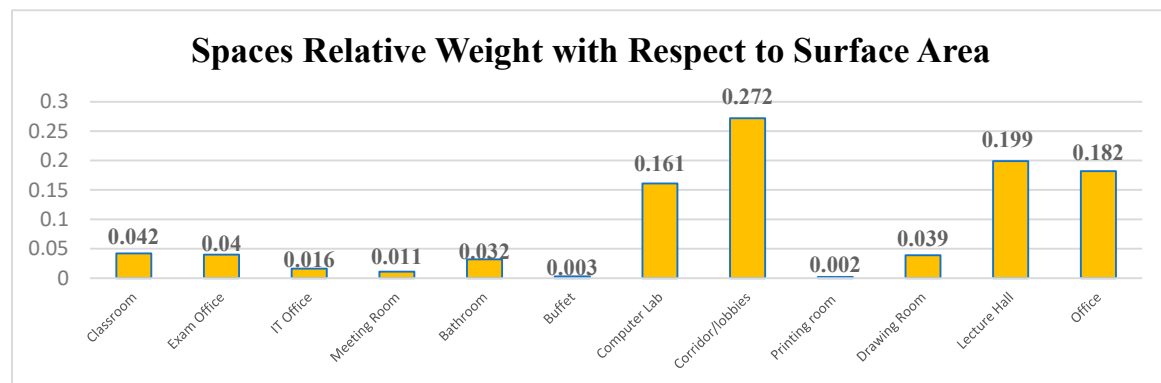


Figure 6. Relative weight of case study spaces with respect to surface area factor.

Table 3. Summary of RW values for categories and subcategories of each case study space.

| Space Type | RW    | Space Category | RW   | Space Sub-Category | RW    |
|------------|-------|----------------|------|--------------------|-------|
| Classroom  | 0.145 | Architectural  | 0.48 | Walls              | 0.124 |
|            |       |                |      | Floors             | 0.128 |
|            |       |                |      | Windows            | 0.119 |
|            |       |                |      | Doors              | 0.114 |
|            |       | Electrical     | 0.36 | Lighting           | 0.139 |
|            |       |                |      | Electrical Devices | 0.121 |
|            |       | Mechanical     | 0.16 | HVAC System        | 0.141 |
|            |       |                |      |                    |       |

Table 3. Cont.

| Space Type        | RW    | Space Category | RW   | Space Sub-Category | RW    |
|-------------------|-------|----------------|------|--------------------|-------|
| TA Offices        | 0.247 | Architectural  | 0.44 | Walls              | 0.123 |
|                   |       |                |      | Floors             | 0.13  |
|                   |       |                |      | Windows            | 0.118 |
|                   |       |                |      | Doors              | 0.12  |
|                   |       | Electrical     | 0.35 | Lighting           | 0.133 |
|                   |       |                |      | Electrical Devices | 0.122 |
|                   |       |                |      | Mechanical         | 0.21  |
| Computer Labs     | 0.096 | Architectural  | 0.16 | Walls              | 0.137 |
|                   |       |                |      | Floors             | 0.1   |
|                   |       |                |      | Windows            | 0.137 |
|                   |       |                |      | Doors              | 0.132 |
|                   |       | Electrical     | 0.55 | Lighting           | 0.195 |
|                   |       |                |      | Electrical Devices | 0.09  |
|                   |       |                |      | Mechanical         | 0.29  |
| Bathrooms         | 0.034 | Architectural  | 0.34 | Walls              | 0.17  |
|                   |       |                |      | Floors             | 0.176 |
|                   |       |                |      | Windows            | 0.156 |
|                   |       |                |      | Doors              | 0.151 |
|                   |       | Mechanical     | 0.32 | Plumbing           | 0.167 |
|                   |       | Electrical     | 0.34 | Lighting           | 0.18  |
| Admin Offices     | 0.198 | Architectural  | 0.42 | Walls              | 0.122 |
|                   |       |                |      | Floors             | 0.124 |
|                   |       |                |      | Windows            | 0.12  |
|                   |       |                |      | Doors              | 0.126 |
|                   |       | Electrical     | 0.4  | Lighting           | 0.124 |
|                   |       |                |      | Electrical Devices | 0.128 |
|                   |       |                |      | Mechanical         | 0.18  |
| Corridors/Lobbies | 0.232 | Architectural  | 0.46 | Walls              | 0.155 |
|                   |       |                |      | Floors             | 0.165 |
|                   |       |                |      | Windows            | 0.114 |
|                   |       | Electrical     | 0.38 | Lighting           | 0.151 |
|                   |       | Mechanical     | 0.16 | HVAC System        | 0.13  |

### 5.2. Deterioration Prediction Results

The application of the Markov chain model enabled the prediction of future condition states for building components under uncertainty. Table 4 represents a one-year time-step interval of computers' probability transition matrix, under the assumption of pure deterioration without maintenance, repair, or replacement. The results demonstrated that components in high-usage spaces are expected to deteriorate at a faster rate compared to those in less frequently used areas. The probabilistic nature of the model provided a

realistic representation of degradation behavior, capturing variability that deterministic approaches often fail to address, as shown in Table 5.

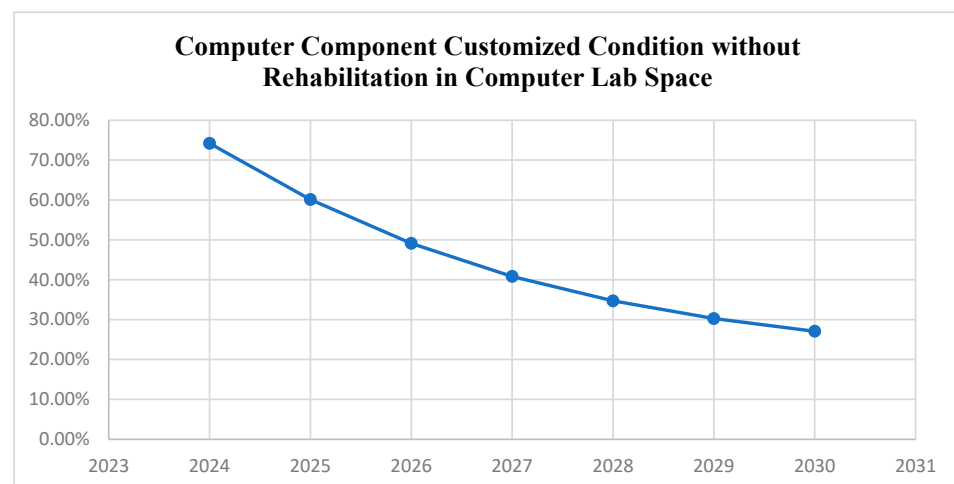
**Table 4.** One-year time-step interval of computers' probability transition matrix.

| One Year Time-Step of Condition States |           |      |      |      |         |
|----------------------------------------|-----------|------|------|------|---------|
| P1                                     | Excellent | Good | Fair | Poor | Failing |
| Excellent                              | 0.62      | 0.1  | 0.28 | 0    | 0       |
| Good                                   | 0         | 0.24 | 0.31 | 0.45 | 0       |
| Fair                                   | 0         | 0    | 0.63 | 0.16 | 0.21    |
| Poor                                   | 0         | 0    | 0    | 0.39 | 0.61    |
| Failing                                | 0         | 0    | 0    | 0    | 1       |

**Table 5.** Customized condition of the “computers” component through years in computer labs.

| Current State of Computers (Computer Lab Space) |                |           |           |           |              |                         |                             |
|-------------------------------------------------|----------------|-----------|-----------|-----------|--------------|-------------------------|-----------------------------|
| Years                                           | 5<br>Excellent | 4<br>Good | 3<br>Fair | 2<br>Poor | 1<br>Failing | Customized<br>Condition | Deterioration<br>Percentage |
| 2023                                            | 0.38           | 0.19      | 0.24      | 0.14      | 0.05         | 4.92                    | 98.31%.                     |
| 2024                                            | 0.23           | 0.08      | 0.31      | 0.18      | 0.18         | 3.71                    | 74.20%                      |
| 2025                                            | 0.15           | 0.04      | 0.29      | 0.16      | 0.36         | 3.00                    | 60.09%                      |
| 2026                                            | 0.09           | 0.02      | 0.24      | 0.13      | 0.52         | 2.46                    | 49.11%                      |
| 2027                                            | 0.06           | 0.01      | 0.18      | 0.09      | 0.65         | 2.04                    | 40.82%                      |
| 2028                                            | 0.03           | 0.01      | 0.14      | 0.07      | 0.75         | 1.74                    | 34.70%                      |
| 2029                                            | 0.02           | 0.01      | 0.09      | 0.05      | 0.82         | 1.51                    | 30.26%                      |
| 2030                                            | 0.01           | 0.01      | 0.07      | 0.04      | 0.87         | 1.35                    | 27.09%                      |

The model successfully generated condition forecasts over defined time intervals, allowing the identification of components approaching critical condition thresholds. This predictive capability supports proactive maintenance planning by enabling interventions to be scheduled before failure occurs. Compared to traditional reactive maintenance approaches, the Markov-based model offers a more structured and forward-looking strategy, particularly in environments with limited historical data, as shown in Figure 7.



**Figure 7.** Customized condition of computers in computer labs without rehabilitation.

### 5.3. Model Development, Maintenance Prioritization, and Planning

By integrating CA, RW, and deterioration prediction outputs, the framework produced a data-driven maintenance prioritization scheme. Components with high deterioration levels and high relative importance were identified as top priorities for intervention. This approach contrasts with conventional practices, where maintenance decisions are often based on immediate failures or subjective judgment. The implementation of the framework within a BIM–FM environment allowed these priorities to be translated into actionable maintenance plans, as shown in Figures 8–10, representing computer components in a computer lab space. This includes detailed information that reduces the potential for conflicts and errors during data export and import of building components. Additionally, the component images assist in identifying the current state of the components and addressing any issues that arise, thus enhancing the maintenance action plan.

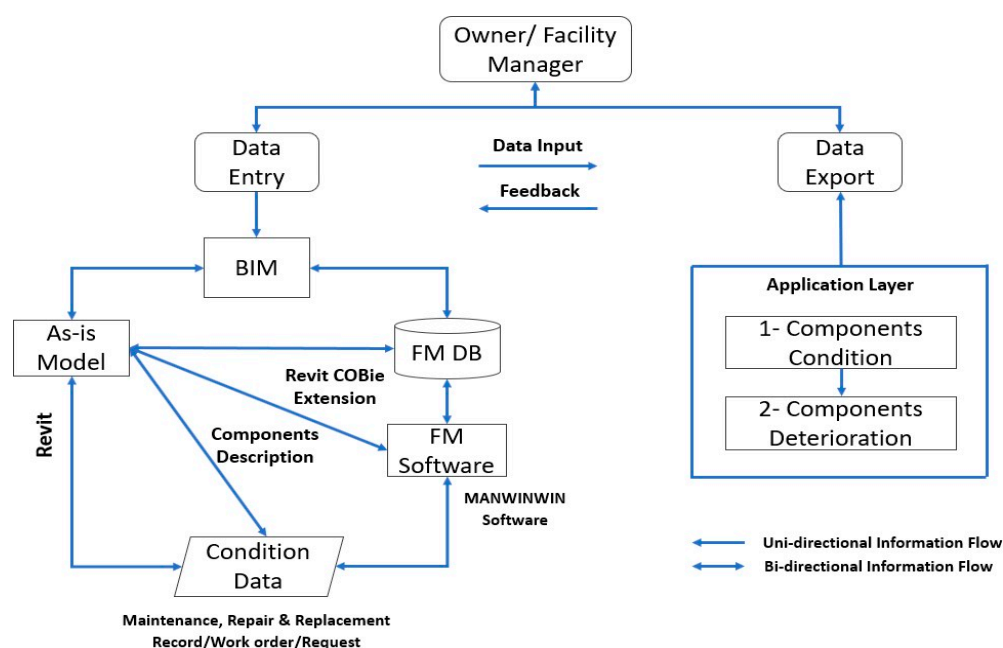


Figure 8. The proposed BIM model framework.

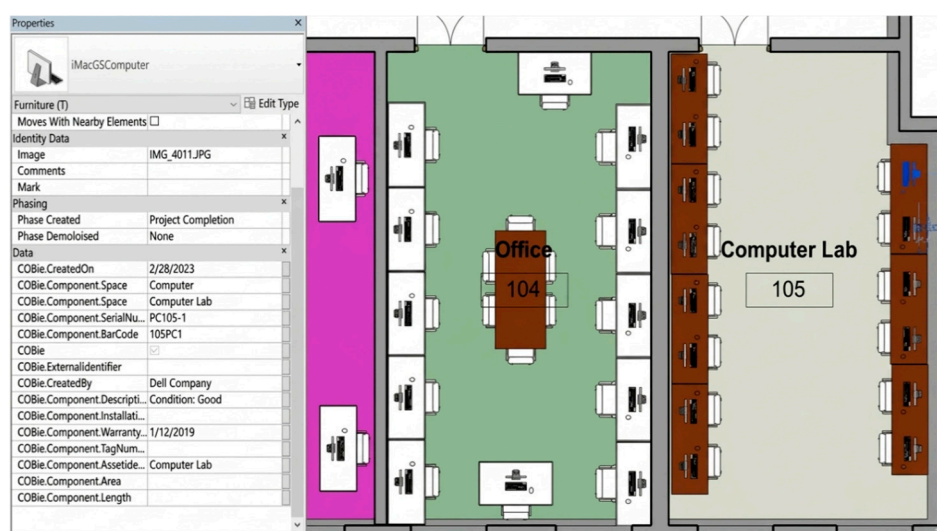
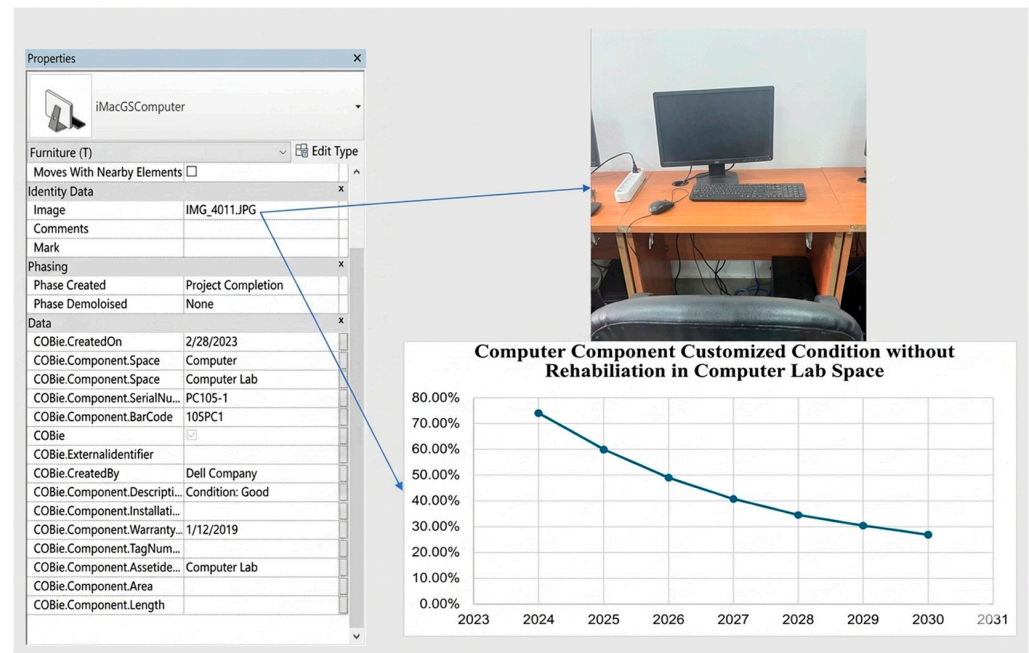


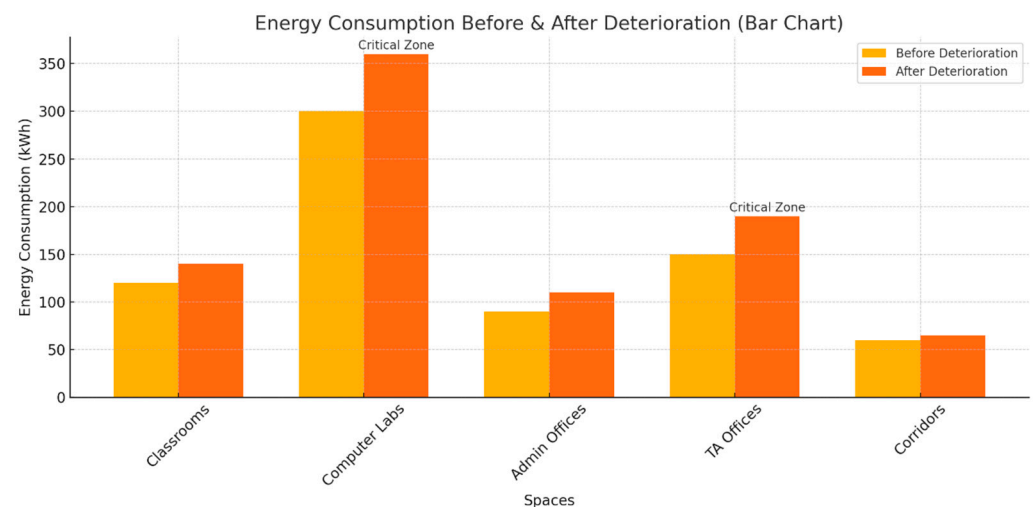
Figure 9. Computer component information using the COBie Extension on a computer lab.



**Figure 10.** Computer properties and image from computer lab space.

#### 5.4. Sustainability Implications

The integration of sustainability metrics provided additional insights into the relationship between component condition and environmental performance. The analysis showed that deteriorated components are associated with increased energy consumption and reduced operational efficiency, as shown in Figure 11, where Table 6 represents the energy consumption data within spaces. By addressing these components through timely maintenance, the framework contributes to improved energy performance and extended component lifespan. This linkage between maintenance and sustainability highlights the importance of incorporating environmental considerations into facility management workflows. Unlike traditional approaches that focus primarily on cost and functionality, the proposed framework enables a more holistic evaluation of building performance, aligning maintenance decisions with sustainability objectives.



**Figure 11.** Energy consumption before and after deterioration.

**Table 6.** Case study energy consumption data.

| Power 1 | Power 2 | Power 3 | Operation Time | Gadget              | Data                                        | Ground Floor (Room Names) |        |        |        |            | Total Power Consumption for Appliance per Floor |
|---------|---------|---------|----------------|---------------------|---------------------------------------------|---------------------------|--------|--------|--------|------------|-------------------------------------------------|
|         |         |         |                |                     |                                             | 101                       | 102    | 103    | 104    | Print Room |                                                 |
| Watts   | Watts   | Watts   | Hours          | Items               | Area (m <sup>2</sup> )                      | 15                        | 47.7   | 74.4   | 50     | 5.5        |                                                 |
|         |         |         |                |                     | Max occupants/day                           | 1                         | 16     | 8      | 14     | 1          |                                                 |
|         |         |         |                |                     | Number                                      | 6                         | 15     | 24     | 12     | 2          | 166                                             |
| 30      | -       | -       | 7              | Light               | Total consumption (Wh)                      | 1260                      | 3150   | 5040   | 2520   | 420        | 34,860                                          |
|         |         |         |                |                     | Number                                      | 1                         | 15     | 8      | 13     | 1          | 88                                              |
| 260     | -       | -       | 5              | PC                  | Average power consumption/day               | 1300                      | 19,500 | 10,400 | 16,900 | 1300       | 114,400                                         |
|         |         |         |                |                     | Number                                      | 1                         | 5      | -      | 6      | -          | 32                                              |
| 100     | -       | -       | 5              | Laptops             | Average power consumption/day               | 500                       | 2500   | -      | 3000   | -          | 16,000                                          |
|         |         |         |                |                     | Number                                      | 1                         | 2      | 3      | 2      | 1          | 21                                              |
| 0.5     | -       | -       | 24             | Firefighting Alarms | Average power consumption/day               | 12                        | 24     | 36     | 24     | 12         | 252                                             |
|         |         |         |                |                     | Total power consumption based on Sunday kwh | 3.22                      | 26.31  | 21.21  | 24.11  | 12.87      | 200.65                                          |

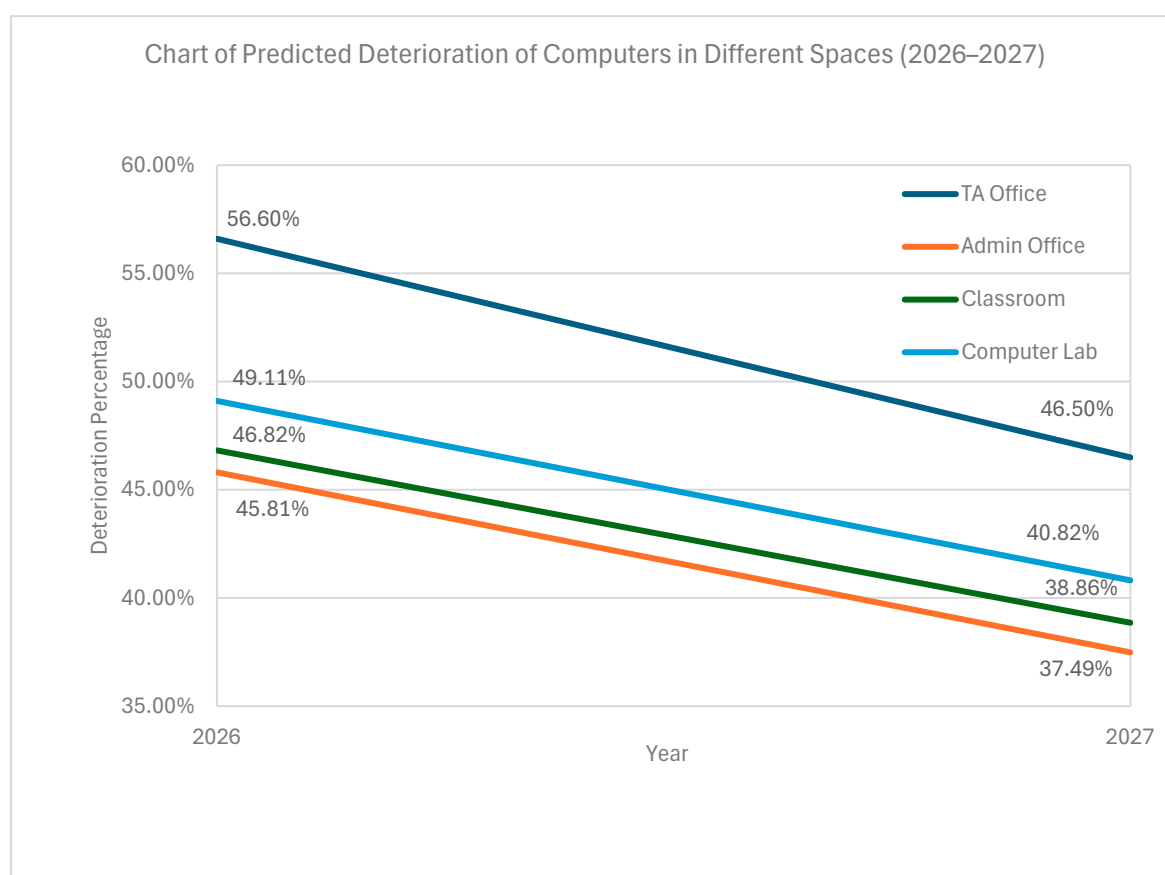
### 5.5. Discussion

The results demonstrate that the proposed framework effectively bridges the gap between condition assessment, predictive modeling, and facility management. The use of a Markov-based approach offers a practical alternative to data-intensive machine learning models, providing reliable predictions with limited data requirements. This makes the framework particularly suitable for educational buildings and similar environments where data availability is constrained. Figure 12 illustrates the annual deterioration progression and prioritization of maintenance activities across TA offices, computer labs, classrooms, and administrative offices. The chart visually demonstrates how the TA office requires immediate intervention in 2026, followed by increasing priority shifts toward computer labs and classroom computers in 2027 as deterioration advances.

Compared to existing BIM–FM implementations, the framework enhances functionality by introducing predictive capabilities and integrating sustainability metrics. It transforms BIM from a static information repository into a dynamic decision support tool. Furthermore, the ability to operate without real-time IoT data addresses a key limitation in current Digital Twin applications, offering a more accessible pathway toward digital transformation. Overall, the findings confirm that integrating CA, RW, DP, and BIM–FM workflows leads to improved maintenance prioritization, enhanced predictive capability, and better alignment with sustainability goals.

Beyond improving maintenance prioritization, the proposed BIM–Markov framework demonstrated tangible economic benefits through its ability to support cost-effective maintenance planning. The framework enables facility managers to prioritize interventions based not only on condition assessment results, deterioration forecasts, and functional importance, but also on maintenance cost implications under constrained budgets. In the case study building at the British University in Egypt (Building A, first floor, 2772 m<sup>2</sup>), the implementation of the predictive maintenance framework was benchmarked against the previously adopted reactive and time-based maintenance approach using facility management records obtained from the FM system during the 2024–2025 assessment period. The analysis revealed that annual maintenance expenditures decreased from EGP 1,250,000 under the reactive maintenance strategy to EGP 975,000 following the implementation of predictive and preventive maintenance schedules generated through the BIM–Markov framework, corresponding to a cost reduction of EGP 275,000, or approximately 22%. These

savings were distributed across multiple building spaces, including computer laboratories, corridors, classrooms, lecture halls, and office areas, reflecting the framework's ability to optimize maintenance timing before critical failures occur. The reduction was calculated as the percentage difference between reactive and preventive maintenance costs relative to the original reactive maintenance expenditure. In addition to cost savings, the framework supports lifecycle-oriented decision-making by reducing unplanned failures, minimizing operational disruptions, extending asset service life, and improving resource allocation efficiency.



**Figure 12.** Predicted deterioration of computers in different spaces (2026–2027).

#### 5.6. Framework Scalability and Applicability

Although the proposed framework was validated using a single educational building case study, its structure is designed to be scalable and adaptable to a broader range of building contexts. The hierarchical asset classification, condition assessment methodology, relative weighting system, and Markov-based deterioration prediction approach are not restricted to educational facilities and can be applied to other building typologies, including healthcare facilities, office buildings, commercial developments, and public infrastructure assets.

The framework can also be extended from individual spaces or floors to entire buildings by expanding the asset hierarchy and incorporating additional building systems and components within the BIM–FM environment. As the framework relies on structured asset information and periodic condition assessments rather than continuous IoT data streams, its implementation remains feasible for large-scale facilities with limited digital infrastructure. These characteristics demonstrate that the framework provides a flexible foundation for supporting predictive maintenance, sustainability assessment, and Digital Twin readiness across a wide range of building types and geographical contexts.

## 6. Contribution

This study makes several significant contributions to the field of facility management and digital transformation in the built environment:

**Integrated Framework Development:** The research proposes a novel Eco-Digital framework that integrates condition assessment, deterioration prediction, BIM, facility management, and sustainability metrics within a unified workflow. This addresses the fragmentation commonly observed in existing approaches.

**Data-Efficient Predictive Modeling:** The study demonstrates the application of a Markov chain model as a practical alternative to machine learning techniques, enabling predictive maintenance in environments with limited data availability.

**Digital Twin Readiness without IoT Dependency:** Unlike many existing frameworks, the proposed approach does not rely on real-time IoT data, making it applicable to a wider range of existing buildings. It provides a realistic pathway for transitioning toward Digital Twin-enabled systems.

**Integration of Sustainability into Maintenance Decision-Making:** The framework incorporates energy and lifecycle performance metrics, linking maintenance strategies with environmental outcomes and promoting holistic sustainability.

**Real-World Validation:** The framework is validated through a real educational building case study, demonstrating its practical applicability, scalability, and effectiveness in improving maintenance planning and decision-making.

**Comparative Advancement over Existing Frameworks:** The proposed framework bridges the gap between BIM–FM systems, Digital Twin readiness models, and Markov-based deterioration prediction approaches by integrating these elements within a single interoperable workflow. This integration enables predictive maintenance, sustainability assessment, and Digital Twin readiness without requiring extensive IoT infrastructure.

## 7. Conclusions

This study presented a BIM-integrated Eco-Digital framework for predictive maintenance and sustainability assessment in educational buildings, supporting their transition toward Digital Twin readiness. The research addressed key limitations in existing facility management practices, including reliance on reactive maintenance, fragmented data systems, and the lack of integrated sustainability considerations. The results demonstrate that combining condition assessment, relative weighting, and Markov-based deterioration prediction within a BIM–FM environment enables structured deterioration forecasting of component performance and more effective maintenance prioritization. The integration of sustainability metrics further enhances decision-making by linking maintenance actions to energy performance and lifecycle impacts.

From a practical perspective, the proposed framework provides a scalable and data-efficient solution for improving facility management in existing buildings, particularly in contexts where advanced digital infrastructure is not available. It offers a clear pathway for transforming static BIM models into dynamic, predictive systems capable of supporting long-term asset performance and sustainability goals. However, the study is subject to several limitations. The reliance on manual inspection introduces potential subjectivity in condition assessment, and the absence of real-time data restricts the dynamic updating of model predictions. In addition, the framework was applied to a single case study, which may limit generalizability across different building types and contexts. Future research should focus on integrating IoT-based data collection, exploring hybrid models that combine statistical and artificial intelligence approaches, and extending the framework to multiple buildings to assess scalability and adaptability. Further work can also investigate

automated condition assessment techniques and enhanced interoperability between BIM and facility management systems.

If IoT sensors are implemented in future work, they would significantly enhance the predictive maintenance framework by supplying continuous, real-time operational data that cannot be captured through manual inspection, using sensors installed on mechanical equipment. These data streams allow automatic generation of alerts, improved accuracy of deterioration forecasting, and real-time updates to the Digital Twin, transforming the model into a self-updating, sensor-driven predictive maintenance environment. Table 7 presents the building components currently assessed through manual inspections and identifies the corresponding components that could be enhanced with IoT sensor technologies in future implementations to support real-time monitoring and predictive maintenance. Although interoperability was achieved through the integration of BIM, COBie, and the FM platform, future developments should focus on strengthening automated data exchange and synchronization between BIM and FM environments. The adoption of open standards and interoperable data protocols could further improve information consistency, reduce manual data handling, and support the transition toward fully integrated Digital Twin ecosystems.

**Table 7.** Manually inspected components and proposed IoT sensor-enabled components.

| Category          | Component                  | Inspected Manually? | Suitable for IoT Sensors? | Type of Sensor                          | Purpose                                                            | How IoT Sensor Output Considered in DT-Model?                                                                                                                                      |
|-------------------|----------------------------|---------------------|---------------------------|-----------------------------------------|--------------------------------------------------------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Architectural     | Walls                      | ✓ Yes               | × No                      | —                                       | Visual defects, cracks, moisture—requires manual or CV inspection. | Periodic image/moisture readings → processed to produce a normalized condition score. That score becomes the current state input to the Markov model (replacing manual rating).    |
|                   | Floors/Tiles               | ✓ Yes               | × No                      | —                                       | Surface deterioration, unevenness—primarily visual/manual.         | Crack/unevenness detection → score output fed into CI. Sudden change flags corrective maintenance.                                                                                 |
|                   | Ceilings                   | ✓ Yes               | × No                      | —                                       | Cracks, and manual                                                 | Visual metrics → convert to condition score; update component's state in BIM and feed Markov model.                                                                                |
| Mechanical (HVAC) | AC Units                   | ✓ Yes               | ✓ Yes                     | Temperature, vibration, airflow sensors | Temperature, and filter status.                                    | Triggers preventive maintenance, and updates COBie properties automatically.                                                                                                       |
|                   | Ducts                      | ✓ Yes               | ✓ Possible                | Airflow sensors                         | Detect blockages, performance reduction.                           | Efficiency metric feeds model as condition score and HVAC components; sudden drops generate FM alarms.                                                                             |
| Electrical        | Lighting Fixtures          | ✓ Yes               | ✓ Yes                     | Smart meters, motion sensors            | Energy consumption, occupancy, failure detection.                  | Update energy consumption metrics in DT, infer remaining useful life (based on on/off cycles), and modify Markov transition probabilities for lighting (usage-driven degradation). |
|                   | Switches & Sockets         | ✓ Yes               | ✓ Possible                | Smart switches                          | Energy usage, overload alerts.                                     | Detect overloads, abnormal leakage. Instant anomalies—corrective maintenance ticket in FM.                                                                                         |
|                   | Computers (Labs & Offices) | ✓ Yes               | ✓ Yes                     | Power consumption, temperature sensors  | Device usage, overheating risk, energy efficiency.                 | These indicators allow DT to predict failures. FM receives auto-work orders for at-risk devices. Energy metrics contribute to eco-sustainability calculations.                     |

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