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# Assessing the Determinants of Maintenance Effectiveness in Aged Buildings Using Structural Equation Modeling: An Empirical Study in Vietnam

Thi-Cam Tien Ngo[1,2], Thanh-Tan Le[1,2], Trung-Hieu Le[3], Duc-Hoc Tran[1,2,*]

[1]Faculty of Civil Engineering, Ho Chi Minh City University of Technology (HCMUT), 268 Ly Thuong Kiet Street, Dien Hong Ward, Ho Chi Minh City, Vietnam

[2]Vietnam National University Ho Chi Minh City, Linh Xuan Ward, Ho Chi Minh City, Vietnam

[3]RIMAS Research Group (Resilience & Innovative Materials for Smart Infrastructures), University of Transport Technology, 54 Trieu Khuc, Thanh Liet, Hanoi, Vietnam

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***Corresponding author:**
Email address:
tdhoc@hcmut.edu.vn

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**Abstract:** Effective management of aging buildings presents significant economic and technical challenges, particularly in large urban centers such as Ho Chi Minh City, Vietnam, where numerous high-rise structures were constructed prior to 1975. Because operation and maintenance can comprise nearly 80% of overall life-cycle costs, pinpointing the factors that impede maintenance effectiveness is of vital importance. The present study constructs and validates a model to examine and quantify the critical factors that hinder Building Maintenance Effectiveness (BME). The study was carried out using Partial Least Squares Structural Equation Modeling (PLS-SEM) with data obtained from 147 valid responses of maintenance experts in Ho Chi Minh City, Vietnam. The suggested model exhibits substantial explanatory capacity, clarifying 74.5% of the variance in BME ($R^2 = 0.745$). The analysis reveals five statistically significant negative determinants: Building Management Factors (BMF), Budget and Financial-Related Factors (BFRF), Technical-Related Factors (TRF), Technology Application-Related Factors (TARF), and Building User-Related Factors (BURF). Among these, deficiencies in technology application (TARF) emerged as the most critical barrier ($f^2 = 0.351$), followed by moderate effects from management (BMF) and financial (BFRF) constraints. The study provides a data-driven analytical framework to support facility managers and policymakers in prioritizing investment resources, while emphasizing technology adoption as the most strategic intervention for optimizing performance and ensuring sustainable development of building assets.

**Keywords:** Building maintenance, Structural equation modeling, Maintenance effectiveness, Building management factors, Maintenance organizations.

## 1. Introduction

In the context of rapid global urbanization, modern cities are increasingly facing mounting pressure to maintain the quality of built infrastructure, particularly for buildings that have been in use for extended periods [1]. The shift from extensive development to sustainable growth has brought issues related to operational performance, structural longevity, and utilization efficiency to the forefront of urban asset management strategies [2]. Existing buildings not only serve as the physical backbone of urban infrastructure but are also closely linked to the social, economic, and environmental dimensions of urban development [3, 4]. However, over time, these structures often experience a decline in both functional performance and structural safety—factors that negatively impact occupants while significantly increasing the lifecycle costs associated with operations, maintenance, and emissions [5].

In the context of sustainable development becoming a top priority in the construction industry, building asset maintenance is increasingly regarded as a strategic component—playing a critical role in enhancing operational efficiency, extending the service life of structures, and managing lifecycle costs [6, 7]. Rather than being perceived merely as a series of routine technical tasks, modern maintenance is approached as a comprehensive management process that integrates operational data, organizational capabilities, and technological readiness to support effective decision-making. However, in practice, many maintenance systems remain reactive, fragmented in terms of resources, and are not yet designed to optimize performance holistically [6]. A fundamental reason for the shortfall lies in the absence of quantitative research that can systematically identify and measure the factors influencing maintenance effectiveness under specific operational conditions [8]. Moreover, empirical evidence suggests that operation and maintenance costs can account for as much as 75–80% of a building's total lifecycle cost—particularly for structures with a design lifespan of approximately 50 years. The analysis underscores the urgent need for a scientifically grounded maintenance management framework, built upon empirical data and quantitative analysis, to enhance cost control and mitigate risks associated with asset degradation over time [6, 7].

Moreover, although numerous studies have addressed individual factors such as maintenance planning, financial resources, personnel competency, or the level of technological support, most existing research has yet to provide a comprehensive theoretical model that captures and empirically tests the integrated relationship between these factors and building maintenance effectiveness (BME) [9-11]. Notably, previous research frameworks often lack the integration of technology as a strategic component in evaluating maintenance effectiveness even though technological readiness has become increasingly critical in modern facility and asset management [10]. The gap highlights the need to develop robust quantitative models capable of simultaneously assessing both tangible factors (e.g., cost, technology, monitoring systems) and intangible ones.

In recent years, the rapid advancement of digital technologies such as artificial intelligence (AI), machine learning (ML), building information modeling (BIM), and sensors within the internet of things (IoT) ecosystem has significantly transformed the approach to building maintenance [12-14]. These technologies not only facilitate real-time collection and processing of technical data but also enable predictive diagnostics, optimization of maintenance schedules, and reduction of operational costs [15-19]. The implementation of BIM for facilities management (BIM-FM) allows for the synchronization of geometric and non-geometric data, thereby enhancing information traceability and control over building conditions. Similarly, machine learning algorithms can uncover nonlinear relationships among technical, operational, and financial variables within the maintenance process. However, these technologies will not be effective unless embedded within a well-structured maintenance strategy that is guided by clear objectives and is adaptable to organizational conditions [3, 8, 20].

Although numerous studies have investigated building maintenance, a comprehensive understanding of the factors influencing maintenance effectiveness remains limited. To date, most research has focused on isolated aspects rather than providing an integrated and empirical evaluation of the combined effects of these factors on the maintenance process. In particular, the role of technology in enhancing maintenance effectiveness has not yet been thoroughly and systematically examined. The study aims to (i) identify the key factors affecting building maintenance effectiveness (BME) and (ii) assess the magnitude and direction of their impacts on the overall performance of maintenance processes. To achieve this, relevant literature was reviewed and analyzed to determine five primary factors influencing maintenance effectiveness. In addition, ten representative criteria were proposed to evaluate the performance of building maintenance processes. A hypothetical model was then developed to validate the influence of these factors on BME. The Structural Equation Modeling (SEM) technique was employed to empirically test the proposed hypotheses and quantify the relationships among the variables, thereby providing deeper insights into how these identified factors contribute to overall maintenance effectiveness. As the global building stock continues to expand, research on building maintenance is expected to play an increasingly important role in promoting the sustainability of built assets [21]. Accordingly, this study not only contributes to the theoretical understanding of building maintenance effectiveness but also provides practical insights for stakeholders on how to integrate technology into maintenance management processes to optimize performance and ensure long-term sustainability.

## 2. Literature review

### 2.1. Criteria for evaluating BME

Improving BME particularly for aging structures requires comprehensive evaluation approaches that simultaneously capture economic, environmental, and social dimensions [3, 22]. Within the given context, the development of a clear and structured set of evaluation criteria plays a foundational role, not only in measuring current performance but also in supporting strategic planning and continuous improvement. A well-defined effectiveness assessment framework enables organizations to identify strengths and weaknesses within the maintenance process, thereby facilitating informed interventions to enhance service quality and optimize the functional value of built assets.

According to Hauashdh, et al. [10] maintenance effectiveness can be measured through core dimensions such as time, cost, quality, safety, productivity, and environmental sustainability. However, recent studies have pointed out that relying solely on the traditional triad of time, cost, and quality is insufficient for driving long term improvement, as these indicators often fail to provide deep insights into the root causes of performance degradation [23]. Consequently, researchers have expanded evaluation frameworks by incorporating additional dimensions such as stakeholder satisfaction, environmental protection, occupational safety, and overall operational efficiency, in order to support continuous improvement throughout the building's lifecycle [24].

Building upon and extending previous studies such as Hauashdh, et al. [10], Ighravwe and Oke [24], and Besiktepe, et al. [25] the study refines and validates a set of ten core criteria, as presented in Table 1, for comprehensively evaluating BME. These criteria have been adapted to reflect the current realities of the construction industry and serve as the foundation for the empirical assessment model developed to measure maintenance effectiveness in a systematic and holistic manner.

### 2.2. Criteria for evaluating BME

BME is a complex construct influenced by a multitude of multidimensional factors, particularly in the context of aging buildings characterized by technical complexity and extended operational lifecycles. Based on a synthesis and analysis of previous studies, five major factor groups have been identified as key determinants of maintenance effectiveness. These include: BMF, BFRF, TRF, TARF, BURF, as detailed in Table 2.

**Table 1.** Criteria for evaluating BME

| Criteria | Description | References |
|---|---|---|
| Cost (BME1) | The extent to which maintenance work is completed within the estimated cost. | [1-3] |
| Time (BME2) | The extent to which maintenance tasks are completed within the planned timeframe. | [1-4] |
| Quality (BME3) | The extent to which maintenance tasks meet the established quality requirements. | [1-4] |
| Technology (BME4) | The extent to which new knowledge is applied, professional skills are enhanced, and advanced technologies are utilized. | [1-3] |
| Regulation (BME5) | The extent to which maintenance tasks are completed in compliance with current legal regulations and industry standards. | [1-4] |
| Users (BME6) | The extent to which maintenance tasks are completed to the satisfaction of building users. | [1-4] |
| Sustainability (BME7) | The extent to which maintenance tasks ensure the safety and long-term sustainability of the infrastructure. | [1-4] |
| Environment (BME8) | The extent to which maintenance activities contribute to significant improvements in the working environment. | [1-4] |
| Productivity (BME9) | The extent to which maintenance activities are completed through effective coordination among stakeholders. | [1-4] |
| Capability (BME10) | The extent to which maintenance requirements are fulfilled, as reflected in the ability to complete tasks on time, accurately, and efficiently. | [1-4] |

BMF play a critical role in determining the effectiveness of maintenance activities, especially in the context of aging buildings that often face severe technical and operational challenges, as outlined in Table 2. A well-structured management system with clearly defined responsibilities assigned to specific individuals within the maintenance process serves as the foundation for task execution efficiency, minimizing confusion and operational errors [6, 21]. The organizational capabilities of the management team, reflected in their ability to develop strategic plans, implement efficient scheduling, and tightly control maintenance activities, contribute to early detection of potential failures, ensure compliance with technical standards, and ultimately maintain operational performance while optimizing lifecycle costs [23, 25-27]. Moreover, strict adherence to scheduled maintenance is a prerequisite for on-time task completion, quality assurance, and enhanced user satisfaction [28]. In practice, building degradation is often directly linked to the absence or inadequate implementation of planned maintenance activities, which accelerates technical system deterioration and leads to reduced performance and shortened service life [29]. Notably, maintenance effectiveness is not solely influenced by technical or financial factors, but also by the degree of coordination and communication among stakeholders including building managers, contractors, and operational units. Effective collaboration among these actors contributes to timely, standards compliant execution of maintenance tasks and reduces the likelihood of latent risks throughout the maintenance lifecycle [6, 30]. Based on the theoretical and empirical foundation, the following hypothesis is proposed H1: BMF have a negative effect on BME.

In the field of building management and operations, BFRF as presented in Table 2, are widely recognized as foundational elements that directly influence the effectiveness of maintenance activities. The proper allocation and efficient management of financial resources are essential prerequisites for maintaining consistent maintenance quality, preventing resource wastage, and strengthening the capacity to respond to risks throughout a building's lifecycle [2, 6, 31]. When maintenance budgets are constrained, activities are often delayed or inadequately executed, resulting in postponed repairs, reduced technical performance, and increased risk of costly emergency interventions in the future [21, 32]. Financial shortages also disrupt the implementation of scheduled maintenance plans, thereby undermining reliability, availability, and operational efficiency. Farahani, et al. [30] emphasized that financial constraints particularly under tight budget conditions represent a key barrier preventing organizations from maintaining optimal maintenance quality. The consequences of limited financial resources extend beyond short-term operational performance, affecting long-term asset life and value, as technical components are more likely to deteriorate without proper upkeep [25, 33]. Based on these theoretical insights and empirical findings, the study proposes the following hypothesis H2: BFRF have a negative effect on BME.

TRF comprising five key attributes as outlined in Table 2, play a critical role in determining the quality and overall effectiveness of building maintenance activities. In practice, many buildings particularly those with long operational histories face significant challenges in implementing maintenance tasks due to the lack of technical solutions appropriate to their structural conditions, location, and accessibility [6, 34]. Moreover, when maintenance processes are not supported by complete, reliable, and up to date technical data such as information on deterioration levels, repair history, or equipment status the accuracy of condition monitoring, assessment, and maintenance planning is compromised, leading to reduced implementation efficiency and a heightened risk of failures [21]. The absence of quality control mechanisms during execution further increases technical errors, resulting in higher repair costs and a shortened building lifespan. In addition, the lack of standardized procedures for risk assessment and technical damage prevention renders maintenance efforts less effective, less adaptive, and more prone to disruption from unexpected incidents [23, 25]. Notably, technical feedback from end users an invaluable source of practical insights is often excluded from the decision making system, which leads to delayed and imprecise maintenance responses [10, 23]. Based on these considerations, the study proposes the following hypothesis H3: TRF have a negative effect on BME.

TARF comprising five key attributes as presented in Table 2, represent core barriers to the digitalization of building maintenance practices. Although advanced technologies such as smart monitoring systems, IoT sensors, and machine learning models have demonstrated considerable potential in enhancing maintenance effectiveness and optimizing lifecycle costs, practical implementation remains limited [6]. The absence of targeted policy support and the high upfront investment costs are major constraints that discourage many organizations particularly those with limited resources from adopting such innovations [23]. Additionally, incompatibilities between new technologies and existing infrastructure often require complex technical adjustments, increasing costs and prolonging integration timelines [6, 23]. Moreover, the implementation capacity is frequently constrained by a lack of skilled personnel and inadequate training programs. Another critical issue lies in the scarcity of rigorous quantitative evaluations of the actual effectiveness of technological applications in real world settings, which results in decision making driven more by intuition than by empirical evidence [27, 35, 36]. Fragmented implementation, lack of long-term strategic vision, and poor systematization continue to hinder the overall effectiveness of technological initiatives in building maintenance [12, 37]. Accordingly, the study proposes the following hypothesis H4: TARF have a negative effect on BME, emphasizing the need to address technological barriers to enable the development of modern, integrated, and effective maintenance solutions.

BURF comprising four key attributes as detailed in Table 2, constitute a critical component influencing the overall effectiveness of building maintenance. User awareness and behavior such as failure to follow technical system usage guidelines or misuse of infrastructure can result in premature damage, reduced operational performance, and shortened lifespan of structural components. The absence of clear signage or specific usage instructions further increases the likelihood of user errors when interacting with technical systems [38-40]. Additionally, delayed or inaccurate reporting of malfunctions to building management often leads to unresolved technical issues, causing widespread damage and unplanned maintenance costs. While such behaviors may appear negligible in the short term, their cumulative effects can significantly impact operational budgets and system performance over time [38-40]. Proper utility usage and timely feedback not only enhance maintenance quality but also foster an effective collaborative environment between users and facility managers, thereby supporting system reliability and operational efficiency [10]. Accordingly, the study proposes the following hypothesis H5: BURF have a negative effect on BME, highlighting the role of user behavior in optimizing maintenance processes and sustaining long-term service quality.

Hypothesis 1 (H1): BMF has a negative effect on BME.

Hypothesis 2 (H2): BFRF has a negative effect on BME.

Hypothesis 3 (H3): TRF has a negative effect on BME.

**Table 2.** Summary of influencing factors and measurement attributes

| Factors | ID | Attribute | References |
|---|---|---|---|
| Building management factor (BMF) | BMF1 | Unclear organization and assignment of maintenance tasks. | [5, 6] |
| | BMF2 | Inadequate maintenance planning and scheduling. | [8, 9] |
| | BMF3 | Deficiencies in inspection and quality assessment. | [3, 4] |
| | BMF4 | Non-compliance with proposed maintenance plans. | [14, 15] |
| | BMF5 | Lack of collaboration and coordination among stakeholders. | [5, 17] |
| | BMF6 | Failure to assess risks or develop contingency plans. | [8, 18] |
| Budget and financial resource factor (BFRF) | BFRF1 | Budget allocations are not aligned with the planned schedule. | [5, 10, 19] |
| | BFRF2 | Insufficient funding to sustain building maintenance activities. | [6, 21] |
| | BFRF3 | Ineffective financial risk management. | [17] |
| | BFRF4 | Delays in budget approval and disbursement. | [4, 32] |

**Table 2.** (continued)

| Factors | ID | Attribute | References |
|---|---|---|---|
| Technical-related factor (TRF) | TRF1 | Lack of adaptive maintenance solutions for aging buildings. | [5, 34] |
| | TRF2 | Maintenance activities lack a reliable and up-to-date database. | [6] |
| | TRF3 | Lack of a mechanism for technical quality control. | [1, 3] |
| | TRF4 | Lack of standardized procedures for risk assessment and damage prevention. | [3, 4] |
| | TRF5 | Lack of mechanisms for user feedback and information updating. | [2, 3] |
| Technology application-related factors (TARF) | TARF1 | Lack of policies to encourage the adoption of technology in maintenance. | [3, 5] |
| | TARF2 | The application of artificial intelligence (AI) in maintenance remains limited. | [24] |
| | TARF3 | There is a lack of resources and expertise to implement technology. | [2, 5] |
| | TARF4 | The initial investment cost is high. | [8, 18, 35] |
| | TARF5 | There is a lack of quantitative assessment of technological effectiveness. | [24, 36] |
| Building user-related factors (BURF) | BURF1 | Building occupants lack adequate knowledge regarding the proper use of facilities. | [37-39] |
| | BURF2 | There is a lack of instructional signage guiding occupants in the proper use of facilities. | [37-39] |
| | BURF3 | Improper use of infrastructure facilities. | [37-39] |
| | BURF4 | Delays in reporting incidents to the building management. | [2] |

Hypothesis 4 (H4): TARF has a negative effect on BME.

Hypothesis 5 (H5): BURF has a negative effect on BME.

The hypothesized structural model is presented in Fig. 1 to assess the impact of five major factor groups on BME, through six reflective constructs connected by directional arrows that represent the causal relationships among latent variables. Specifically, the constructs BMF, BFRF, TRF, TARF, and BURF are measured using 24 observed indicators (BMF1–BMF6, BFRF1–BFRF4, TRF1–TRF5, TARF1–TARF5, BURF1–BURF4), while the dependent construct BME is assessed using 10 specific criteria (BME1–BME10), as detailed Table 1 and Table 2. The model not only provides a comprehensive depiction of the factors influencing maintenance effectiveness but also establishes a foundation for empirically testing the theoretical relationships using PLS-SEM, thereby offering a data-driven basis for optimizing building maintenance strategies.

## 3. Research methodology

### 3.1. Research framework

The research process was systematically designed and is illustrated in Fig. 2. Through an in-depth examination of existing literature, the research identified key influencing factors and their associated observed variables, which served as the basis for creating five proposed constructs: BMF, BFRF, TRF, TARF, and BURF, along with the dependent variable, BME. These constructs were then employed to design the survey questionnaire.

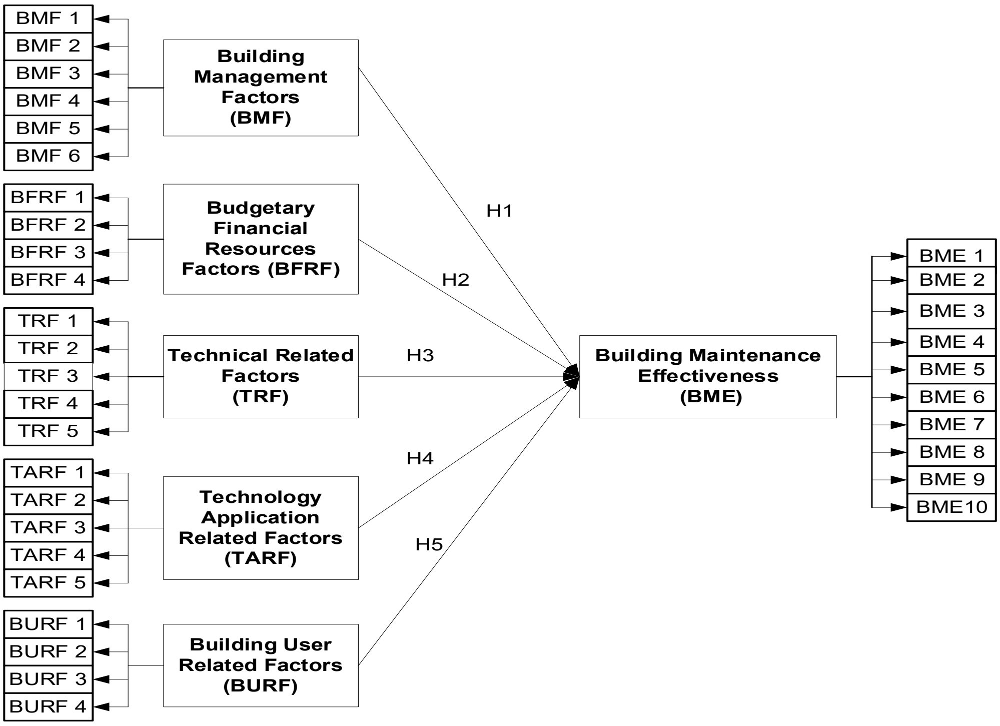


**Fig. 1.** Research model of the relationships among factors

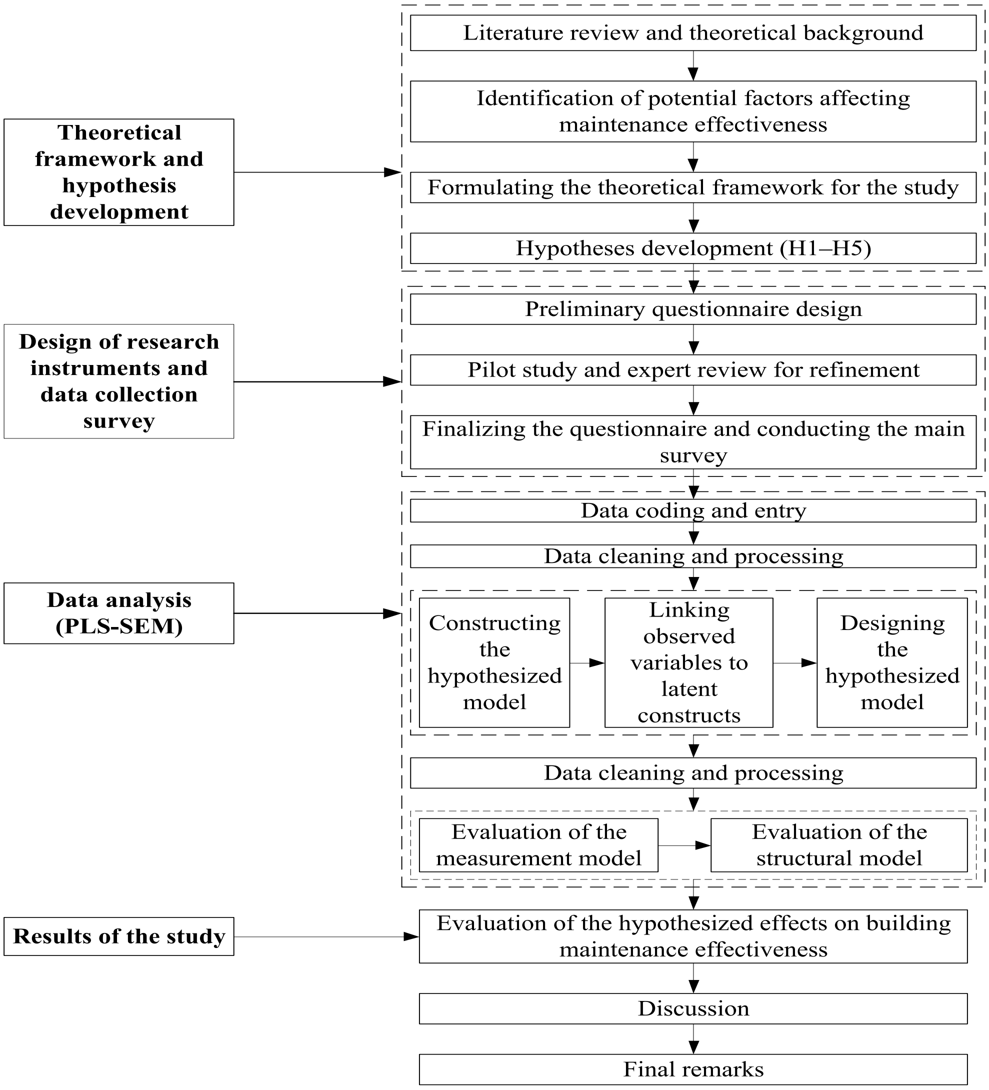


**Fig. 2.** Research Process

The measurement instrument was validated through a pilot study involving Vietnamese building maintenance experts from both academic and professional domains. After the questionnaire was revised and finalized, the main survey was administered to gather empirical data. SEM was employed to analyze and assess the extent to which the five identified factors influence BME. Finally, drawing on the analytical results, the study formulated conclusions, practical implications, acknowledged limitations, and proposed directions for future research.

### 3.2. Case study research strategy

The research makes use of a case study strategy to explore in depth within an actual context. Three criteria for selecting case studies were established: (1) maintenance must be carried out by a specialized organization; (2) the organization must be responsible for all types of maintenance within its scope of operation; and (3) survey participants must be willing to share information regarding the factors influencing work effectiveness.

Based on these criteria, 25 buildings constructed before 1975 in Ho Chi Minh City, Vietnam, were selected. In these buildings, the Management Board was responsible for planning, monitoring activities, and managing maintenance contracts, while implementation was assigned to seven contractors responsible for different areas. The chosen case study not only met all predefined criteria but also ensured representativeness and suitability for an in-depth investigation.

### 3.3. Data collection

The survey methodology employed in this study was designed to test the proposed hypotheses. The survey questionnaire was developed based on the data and structure presented in Table 1 and Table 2. All measurement indicators, including items and reference sources, were carefully adjusted and are presented in detail in Table 1 and Table 2. Prior to conducting the survey, the questionnaire was rigorously tested for content validity to ensure that the concepts were accurately represented and appropriately measured. The study applied six conceptual frameworks, with each survey item assessed using a 5-point Likert scale [41]. Detailed descriptions of these frameworks and the corresponding factor loading values are provided in Fig. 3. The questionnaire validation process involved consultation with an expert panel, which included experienced building maintenance specialists and potential study participants. The panel provided objective feedback and valuable insights, helping to address potential biases arising from the questionnaire developers' familiarity with the topic, which could lead to overlooking important aspects during the design process. Specifically, experts were instructed to identify issues such as unclear phrasing and leading questions. The feedback received played a critical role in refining the phrasing, enhancing content validity, and improving the structural coherence of the questions. To support the research, the survey tool was adjusted based on input from a group of experts with expertise in building maintenance. The survey targeted various participant groups, including building management teams, contractors, engineers, inspectors, and technicians. Altogether, 170 questionnaires were issued, and 147 valid replies were obtained, corresponding to a response rate of 86.5%.

### 3.4. Data Analysis Using Structural Equation Modeling (SEM)

Structural Equation Modeling (SEM) plays a critical role in empirical research within the construction industry, particularly in analyzing and assessing the factors influencing maintenance performance. This method provides detailed insights into the interactions between variables, facilitating the identification and testing of relationships through the SEM framework. The approach consists of two main stages of analysis: evaluating the relationships between observed indicators and latent constructs, while simultaneously testing the hypothesized links between constructs [42]. The measurement model, known as the outer model, clarifies the relationships between the constructs and their corresponding indicators. Conversely, the structural model, or inner model, is dedicated to analyzing the relationships between constructs [43]. In practice, SEM utilizes SmartPLS 3, an advanced software tool designed for effective Partial Least Squares (PLS) modeling analysis. The analysis process involves several key steps, beginning with data input, followed by data processing, model evaluation, and ultimately, reporting the results. Fig. 2 illustrates the SEM workflow, structured around four main steps: data input, data processing, model evaluation, and result reporting. This structured approach allows researchers to assess the validity and reliability of the model, thereby facilitating the drawing of meaningful conclusions from the research data.

## 4. Results of the Study

### 4.1. Measurement Model Evaluation

#### 4.1.1. Reliability Assessment

Hair, et al. [43] indicate that the consistency of constructs is measured through two main techniques: Composite Reliability (CR) and Cronbach's alpha (α). To establish acceptable reliability, both techniques must exceed the threshold of 0.70. In this regard, CR is considered more accurate due to its weighted nature, unlike Cronbach's alpha, which assumes equal contribution from all items. Therefore, CR is generally the preferred choice for reporting reliable results. In this study, both Composite Reliability (CR) and Cronbach's alpha were employed to assess the internal consistency of the constructs in the model. The reliability of a construct reflects the extent to which the observed variables reliably represent the underlying concept being measured. The results show that all CR values exceeded the recommended threshold of 0.70, ranging from 0.867 to 0.944. Similarly, the Cronbach's alpha values also surpassed the 0.70 threshold, ranging from 0.796 to 0.934. These findings, summarized in Table 3, confirm that the reliability of all constructs used in the study is acceptable.

**Table 3.** Reliability

| | Cronbach's alpha | Composite reliability (CR) | Average variance extracted (AVE) |
|---|---|---|---|
| BFRF | 0.796 | 0.867 | 0.620 |
| BME | 0.934 | 0.944 | 0.628 |
| BMF | 0.878 | 0.907 | 0.621 |
| BURF | 0.822 | 0.882 | 0.651 |
| TARF | 0.868 | 0.905 | 0.655 |
| TRF | 0.845 | 0.889 | 0.617 |

#### 4.1.2. Measurement Validity

After assessing reliability, the data were analyzed to evaluate the validity of the measurement model. Factor loadings serve as a key measure to determine the reliability of each item within a construct, reflecting the degree of association among the items within the same construct. The higher the factor loading, the greater the consistency among the items. Each item was analyzed for validity based on its relationship with the corresponding latent variables. Items with factor loadings below 0.4 were removed, while those with loadings between 0.4 and 0.7 could be retained in exploratory research, provided that the Average Variance Extracted (AVE) met the required threshold. Fig. 3 presents the factor loadings for this study, ranging from 0.724 to 0.850, with all core structural factors exceeding the 0.7 threshold, in line with findings from previous studies [44-46]. The percentage of variance explained by the observed variables within a construct is quantified by the Average Variance Extracted (AVE). According to Hair, et al. [43], the AVE value must be at least 0.50, confirming that the latent variable explains more than half of the variance in its indicators. In this study, the AVE values range from 0.617 to 0.655, surpassing the widely accepted threshold of 0.50, as shown in Table 3. This indicates full and significant convergent validity, supporting the appropriateness of using all constructs within the scope of the study.

Discriminant validity is typically assessed by comparing the square root of the Average Variance Extracted (AVE) with the highest squared correlation between a construct and other latent constructs in the model. The square root of the AVE for each construct must be greater than the corresponding correlation values to establish discriminant validity Hair, et al. [43]. Table 4 presents the square root of the AVE for each construct in this study. The results indicate that the square root of the AVE for each construct is statistically significant and exceeds its correlation with all other constructs, thereby meeting the criteria for establishing discriminant validity.

### 4.2. Structural Model Evaluation

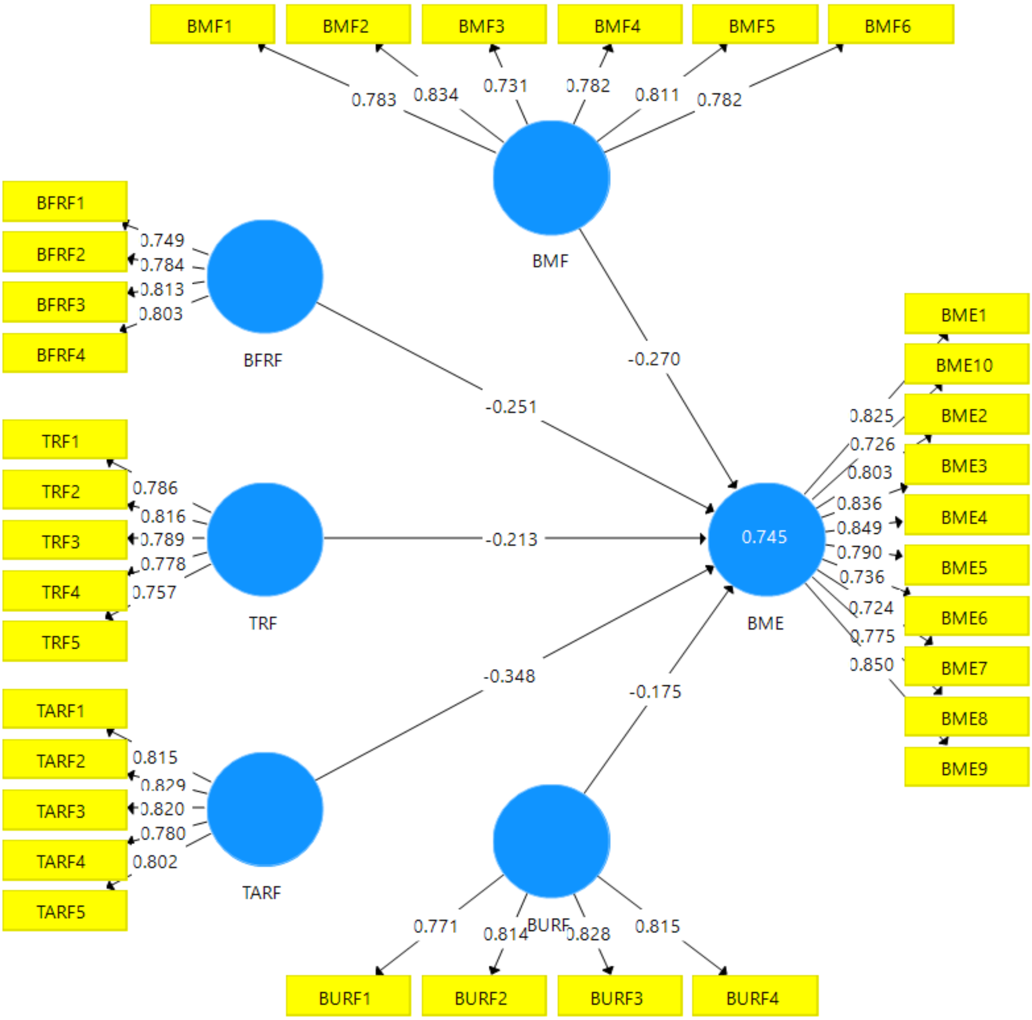


**Fig. 3.** Results of the PLS-SEM Structural Model Analysis

**Table 4.** Fornell-Larcker Criterion

| | BFRF | BME | BMF | BURF | TARF | TRF |
|---|---|---|---|---|---|---|
| BFRF | 0.788 | | | | | |
| BME | -0.513 | 0.793 | | | | |
| BMF | 0.122 | -0.579 | 0.788 | | | |
| BURF | 0.412 | -0.586 | 0.273 | 0.807 | | |
| TARF | 0.227 | -0.654 | 0.447 | 0.332 | 0.809 | |
| TRF | 0.366 | -0.610 | 0.348 | 0.554 | 0.328 | 0.785 |

Following the confirmation of the measurement model's validity, the structural model was analyzed to test the proposed hypotheses. The analysis adhered to four principal criteria highlighted by Hair, et al. [43] and previous research [46-48], which include the coefficient of determination ($R^2$), predictive relevance ($Q^2$), effect size ($f^2$), and results from bootstrapping.

#### 4.2.1. Coefficient of Determination ($R^2$)

The coefficient of determination ($R^2$) represents the share of variance in the dependent construct BME, that is explained by the independent variables in the model. According to Hair, et al. [43], an $R^2$ of 0.75 is considered strong, 0.50 moderate, and 0.25 weak. Similarly, [46-48] suggest that values greater than 0.67 are high, between 0.33 and 0.67 are moderate, between 0.19 and 0.33 are weak, and those below 0.19 are unacceptable. In this research, the model's $R^2$ was 0.745, demonstrating that the five predictors—BMF, BFRF, TRF, TARF, and BURF—explained 74.5% of the variance in BME. This explanatory power is deemed substantial, reinforcing the strength of the structural model.

#### 4.2.2. Effect Size ($f^2$)

To evaluate the contribution of each independent factor to the variance in the dependent construct, the $f^2$ statistic was utilized. According to Hair, et al. [43], values of 0.02, 0.15, and 0.35 denote small, medium, and large effects. The findings in Table 5 reveal that TARF had a strong effect on BME ($f^2$ = 0.351). In contrast, BMF ($f^2$ = 0.215) and BFRF ($f^2$ = 0.197) indicated moderate influences, whereas TRF ($f^2$ = 0.111) and BURF ($f^2$ = 0.075) reflected small impacts on BME.

**Table 5.** Results of Effect Size ($f^2$)

| Relationship | Effect size ($f^2$) | |
|---|---|---|
| | Value | Effect |
| BMF -> BME | 0.215 | Moderate Effect |
| BFRF -> BME | 0.197 | Moderate Effect |
| TRF -> BME | 0.111 | Small Effect |
| TARF -> BME | 0.351 | Strong Effect |
| BURF -> BME | 0.075 | Small Effect |

#### 4.2.3. Predictive Relevance ($Q^2$)

The Stone–Geisser $Q^2$ statistic was used to evaluate the model's predictive relevance. As noted by Hair, et al. [43], a $Q^2$ value above zero suggests that the model possesses predictive ability for the dependent construct. Table 6 shows that the $Q^2$ for BME was 0.463, obtained through SmartPLS. Since this value is greater than zero, it indicates that the model exhibits acceptable predictive relevance.

**Table 6.** Predictive Relevance ($Q^2$)

| Relationship | Predictive Relevance ($Q^2$) | |
|---|---|---|
| | Value | Effect |
| BMF -> BME | 0.463 | Confirming Predictive Relevance |
| BFRF -> BME | 0.369 | Confirming Predictive Relevance |
| TRF -> BME | 0.424 | Confirming Predictive Relevance |
| TARF -> BME | 0.477 | Confirming Predictive Relevance |
| BURF -> BME | 0.409 | Confirming Predictive Relevance |

#### 4.2.4. Hypothesis Testing (Bootstrapping)

The study applied a bootstrapping technique with 5,000 resamples to determine the statistical significance of path coefficients and to examine the research hypotheses. Following conventional practice, p-values were presented to capture the probability of mistakenly rejecting the null hypothesis, an approach adopted here [45]. Hypotheses were therefore evaluated on the basis of p-values, with acceptance criteria set at $p < 0.05$. Results in Table 7 reveal that all five hypotheses were strongly supported, with significance levels at $p < 0.01$.

Hypothesis 1 (H1): The structural model analysis demonstrates that BMF negatively influences BME, and the effect is statistically significant ($p < 0.001$).

Hypothesis 2 (H2): The structural model analysis demonstrates that BFRF negatively influences BME, and the effect is statistically significant ($p < 0.001$).

Hypothesis 3 (H3): The structural model analysis demonstrates that TRF negatively influences BME, and the effect is statistically significant ($p < 0.001$).

**Table 7.** Evaluation Results

| Hypothesis | Relationship | Beta Coefficient (β) | T-statistics | P-values | Result |
|---|---|---|---|---|---|
| H1 | BMF -> BME | 0.045 | 6.055 | 0.000 | Supported |
| H2 | BFRF -> BME | 0.049 | 5.169 | 0.000 | Supported |
| H3 | TRF -> BME | 0.054 | 3.968 | 0.000 | Supported |
| H4 | TARF -> BME | 0.053 | 6.512 | 0.000 | Supported |
| H5 | BURF -> BME | 0.058 | 2.993 | 0.003 | Supported |

Hypothesis 4 (H4): The structural model analysis demonstrates that TARF negatively influences BME, and the effect is statistically significant ($p < 0.001$).

Hypothesis 5 (H5): The structural model analysis demonstrates that BURF negatively influences BME, and the effect is statistically significant ($p = 0.003$).

## 5. Discussion

The study results provide insights into how maintenance organizations can effectively implement building maintenance activities. The analysis examined the factors influencing maintenance effectiveness, including the specific attributes of each factor. The findings indicate a statistically significant negative relationship between TARF and BME, thereby supporting hypothesis H4. Furthermore, the impact of TARF on BME was identified as strong, highlighting the critical role of technology adoption in enhancing maintenance performance. These findings are consistent with and reinforced by previous studies, as discussed in Section 2, where the relationship between technology attributes and building maintenance effectiveness was anticipated. Specifically, the study by Dzulkifli, et al. [23] emphasized that failure to adopt new technologies during maintenance can reduce the overall performance of building maintenance operations, underscoring the importance of integrating modern technological solutions to optimize maintenance effectiveness.

Additionally, the study identified a negative relationship between BMF and BME. Although the effect was moderate, the results still support hypothesis H1, indicating that the structure and management practices of maintenance organizations can significantly influence maintenance performance. These results align with the findings of Pärn, et al. [49], who suggested that organizational structure can affect the effectiveness of building maintenance services. Moreover, the current findings support Ning [50] assertion that an organization’s ability to deliver services effectively, particularly in competitive environments, depends on the selection of qualified contractors, highlighting that organizational structure and task allocation can determine the effectiveness of building maintenance services. The emphasizes the importance of establishing a rational management structure combined with the selection of competent maintenance resources to optimize effectiveness and ensure the success criteria of building maintenance operations.

Regarding hypothesis H2, the results indicate a statistically significant negative relationship between BFRF and BME, with a moderate effect. These findings reinforce theoretical assumptions from previous studies, which suggest that financial resource attributes play a critical role in achieving successful building maintenance outcomes [2, 31, 51]. Zolkafli, et al. [52] noted that the absence of standardized guidance for planned maintenance budgets may result in uncoordinated maintenance implementation, negatively impacting overall effectiveness. Consequently, improving and systematizing budget allocation methods is imperative to ensure that maintenance activities are conducted efficiently and on schedule. The demonstrates that financial resource management involves not only the level of funding but also the implementation of monitoring, planning, and appropriate allocation measures to optimize building maintenance effectiveness.

The study results show that TRF have a negative but significant effect on BME, supporting hypothesis H3. The impact of TRF on BME was identified as small, suggesting that although existing technical resources may not have been fully optimized, they still exert a certain influence on maintenance effectiveness. The findings emphasize that maintenance organizations need to strategically improve and integrate technical resources [23]. Applying advanced technical solutions in conjunction with modern technology in maintenance can optimize operational processes, enhance work quality, and contribute to improving overall building maintenance effectiveness in the long term.

Finally, the results indicate a statistically significant negative relationship between BURF and BME, supporting hypothesis H5. The effect of BURF on BME was small but underscores the importance of users in the maintenance process. Previous studies have demonstrated that building users significantly influence maintenance effectiveness [53]. Au-Yong, et al. [39] emphasized that this effect depends on user behavior and awareness. Specifically, users' understanding of how to utilize building facilities and the timeliness of issue reporting can directly affect maintenance costs and task completion time. The study confirms that high levels of user awareness and cooperation are critical for ensuring effective maintenance services. In other words, maintenance organizations should focus on interaction and coordination with building users, as such cooperation contributes to enhanced effectiveness and quality of maintenance activities.

## 6. Conclusion

### 6.1. Theoretical implications

Empirical evidence from maintenance organizations within the construction industry has demonstrated that building maintenance management is not only an important economic concern but also directly impacts the sustainability of buildings. Theoretical literature on construction management, along with perspectives from industry stakeholders, provides a solid foundation for this research. The findings indicate that existing buildings represent significant economic assets, and effective maintenance can enhance their value and extend their service life. When properly implemented, maintenance activities not only preserve but also improve building operational performance.

The study identified key factors influencing the building maintenance process, offering a foundation for a deeper understanding of elements that enhance maintenance effectiveness. The factors serve as a basis for further research and can be adapted to different contextual settings. A critical aspect clarified by the study is the set of criteria used to evaluate building maintenance effectiveness, which was developed based on prior research and the latest industry trends. These criteria reflect current needs and also encompass sustainability considerations, which are particularly important in the contemporary context. Furthermore, the research emphasizes that the application of technology in building maintenance is not only a quality improvement measure but also yields superior effectiveness compared to traditional methods. Advanced maintenance technologies, such as intelligent monitoring systems and digital solutions, optimize maintenance processes while reducing costs and execution time. The adoption of the latest technological trends not only enhances maintenance effectiveness but also contributes significantly to environmental protection and the sustainability of buildings. An important aspect highlighted by the study is the integration of effective maintenance activities with the capability to monitor maintenance performance efficiently. The implementation of advanced technologies enables maintenance organizations to track, analyze, and adjust maintenance processes accurately and in a timely manner, thereby improving performance and achieving strategic objectives. This not only optimizes maintenance procedures but also delivers long-term benefits for stakeholders and enhances the overall effectiveness of building operations.

### 6.2. Implication for practice

The study addresses the growing interest of governments, policymakers, local authorities, and organizations in building maintenance. It focuses on tackling current key factors and examining their impacts on the Building Maintenance Management System. From a managerial perspective, the study contributes to enhancing building maintenance effectiveness by providing practical guidance for maintenance managers on linking identified influencing factors to their effects on maintenance performance. Such integration can foster active engagement of other stakeholders in the field of building maintenance, thereby facilitating the achievement of effective maintenance outcomes. Empirical evidence from the study provides a foundation for maintenance organizations to optimize and develop strategic decisions related to organizational structure, financial resources, technical capabilities, technological capacity, and user collaboration. This not only enhances maintenance effectiveness but also improves overall building operational performance. The research also delivers valuable insights for stakeholders in the building maintenance sector, raising awareness on how to implement maintenance efficiently. This contributes to extending building lifespan, ensuring occupant safety, and optimizing user satisfaction. Furthermore, the study develops a model that clearly explains barriers and challenges in the construction industry while providing a concrete roadmap for the effective execution of building maintenance activities. Using this model, maintenance organizations can systematically identify factors influencing maintenance effectiveness and implement strategic measures to improve operational performance, thereby achieving the targeted maintenance outcomes. In summary, the study holds significant implications for building sustainability and offers practical benefits to stakeholders in the building maintenance sector. Maintenance organizations, managers, engineers, designers, and other stakeholders can apply the findings to optimize building maintenance processes. Additionally, the study opens avenues for future research, contributing to the long-term development of the building maintenance industry.

However, this study is not without limitations. The data were collected exclusively from pre-1975 residential buildings in Ho Chi Minh City, which may limit the generalizability of the findings to other building types or urban contexts. Future research should consider expanding the scope to include more diverse building categories and different geographical regions to validate and refine the proposed model across broader contexts.

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