

# An Integrated Multi-Attribute Score Model for Evaluating the Performance of Smart Building Systems

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**Abstract:** The assessment of building performance plays a crucial role in achieving sustainability objectives within the construction industry. In recent years, stakeholders have been increasingly focused on evaluating smart buildings (SBs) performance. Numerous methods, criteria, and tools have been developed to measure performance, but most of them primarily concentrate on the overall building level, neglecting the system level of buildings. To tackle this complexity and promote sustainability, it is essential to establish systematic, comprehensive, and practical approaches for evaluating smart building performance. This study proposes an evaluation model for smart buildings performance, encompassing 24 core performance indicators at both the whole building and system levels. The relevance and validity of these indicators were evaluated through a questionnaire survey, along with input from sustainable building experts. This research is part of a broader project aimed at developing a decision support system to assess sustainable building performance and enhance the sustainability of building projects.

**Keywords:** smart buildings; building performance; performance indicators, evaluation model.

## 1. Introduction

The concept of smart buildings (SBs) is rapidly gaining popularity and is now an integral part of the design and development process of buildings. This trend is attributed to the capacity of SB to elevate the comfort and well-being of occupants through user-focused architectural design and continuous technological advancements [1, 2]. Smart buildings are increasingly recognized as a viable solution for enhancing building performance. The recognition of environmental pollution, depletion of natural resources, and related social issues has led to a global focus on sustainable building performance. Buildings are among the largest users of natural resources and contribute significantly to greenhouse gas emissions. Merabet et al. (2021) [3] highlight that buildings globally consume substantial primary energy, largely due to the demand for improved thermal comfort provided by Heating, Ventilation, and Air-Conditioning (HVAC) systems. It is anticipated that sustainable performance

will play a significant role in evaluating the viability of a construction project in terms of its overall performance throughout its life cycle.

According to Bajer (2018) [4], smart buildings employ information technology to link a range of subsystems, enabling them to exchange data to enhance the overall performance of the building. The interaction among specific subsystems tends to be more uniform. The integration of data in smart structures extends beyond the components located inside the building. SB engages with the information technology systems of utility suppliers or emergency services, alongside specific applications designed to aid in the management of facilities (Fig. 1).

SBs have also demonstrated an immense ability to implement sustainable design strategies to improve building performance and ensure occupant comfort [5-7]. Despite the numerous advantages of SBs, their widespread adoption in Oman has not been as rapid as anticipated. Al Mughairi et al. (2023) [8] attribute this to a lack of information and expertise in thoroughly

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Fig. 1 Smart building data integration layers [4].

evaluating the performance of SBs to assist all professionals involved in the project design phase. Ozadowicz (2024) [10] further supports this assertion by highlighting the challenges in understanding SB systems, hindering the realization of their full potential.

Apanaviciene et al. (2020) [9] emphasize the importance of conducting research in the field to unlock the true capabilities of SBs, showcasing the current advancements and future directions through a conceptual model developed in Fig. 2.

*External Environment - SMART CITY*

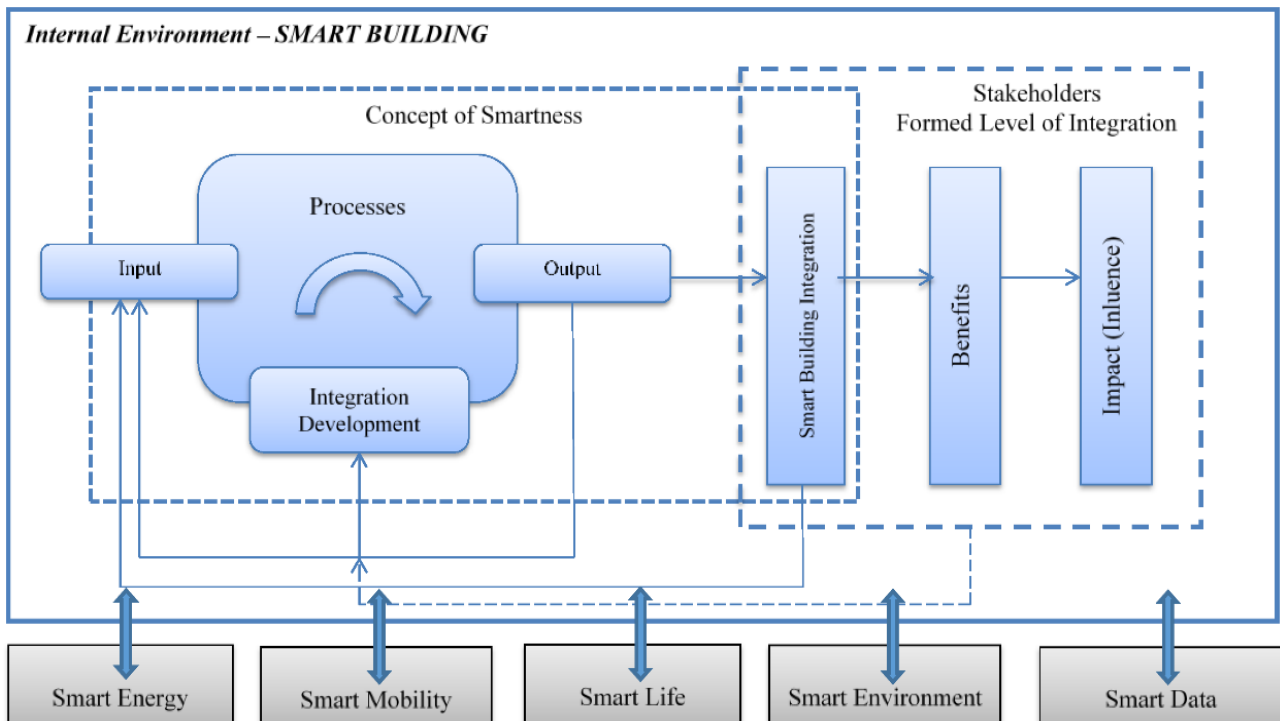


Fig. 2 Theoretical model of smart building integration [9].

It is imperative to evaluate and quantify the performance of smart buildings to meet the increasing demands of clients, professionals, and occupants. This study introduces a scoring model that combines the analytic hierarchy process (AHP) and preference degree approach (PDA) within a fuzzy environment for smart building assessment. The fuzzy AHP is used to calculate the local weights of performance metrics and the ultimate weights of smart building options. As the final weights are represented as fuzzy numbers, fuzzy PDA is applied to rank smart buildings accordingly. Ultimately, the fuzzy AHP-fuzzy PDA method is suggested for the evaluation and measurement of the performance of five smart building alternatives in Oman.

## 2. Multi-attribute Assessment Approach

This article presents a summary of the research conducted to create a model for evaluating and quantifying the effectiveness of SBs. The study proposes a set of essential performance metrics that are refined using the analytical hierarchical process (AHP), a decision support framework suitable for assessing and measuring SB performance. The specific approach involves identifying the key performance metrics and optimizing them through an expert questionnaire survey.

### 2.1 Key Performance Metrics

Two primary concerns were considered when developing a set of performance metrics. Firstly, the purpose for which this set of metrics will be utilized was considered. Secondly, the extent to which any set of metrics can encompass the performance of SBs was examined. Since SBs are complex systems composed of various components, the most effective approach to analyze them is to break down the system into its elements. To identify the critical metrics required to assess the performance of an SB system, a comprehensive survey was conducted. The main metrics were gathered from eight “quality environment modules” (QEMs) labelled as M1 to M8. These modules include: M1 — Environmental and energy, M2 — Space utilization and flexibility, M3

— Cost effectiveness, M4 — Human comfort, M5 — Working efficiency, M6 — Safety and security, M7 — Culture, and M8 — Technological factors. These metrics are further classified under the sub-system in Table 1.

The performance metrics that have been identified primarily pertain to the capacity of buildings and their component systems to maintain and improve the functionality for which they were designed. When making decisions, it is crucial to choose metrics that can be widely applied for assessing and measuring the performance of SBs.

### 2.2 Data Collection and Sample

According to the metrics presented in Table 1, a survey was conducted to investigate the perspective of building designers in Oman regarding the significance of these metrics for assessing the performance of SBs. The survey initially gathered background information from the respondents and their respective organizations. Subsequently, the respondents were asked to rate the importance of the derived metrics on a scale of 1 to 5, with 1 indicating the least importance and 5 indicating the utmost importance. The survey sample consisted of architects and engineers listed in the Oman Society of Engineers (OSE) database, as well as top engineering consultants in Oman. A total of 120 questionnaires were distributed for completion, and 32 valid responses were received, resulting in a response rate of 26.7%.

### 2.3 Criteria Importance Rating

To ensure consistent results over time, a reliability analysis was conducted using the internal consistency method to measure the criteria on a rating scale of 1-5. Cronbach’s alpha was calculated to assess the internal consistency reliability of the scale. The alpha reliability coefficient typically ranges from 0 to 1, with a higher value indicating greater internal consistency reliability. All alpha values for the sub-systems exceeded 0.7, indicating that all reliability coefficients were acceptable, and the internal consistency of the criteria included in the scale was excellent.

**Table 1 Identified key performance metrics (KPMs).**

	Quality environment modules (QEMs)	Subsystem	Key Performance Indicators (KPIs)
1	Environmental and energy (M1)	Environmental metrics group (En-KPMs)	Greenhouse Gas Emissions (GHG) [EN 1] Energy and Natural Resources [EN2] Water conservation [EN3] Materials used, durability, and waste [EN4] Land use and site selection [EN5] Transport and accessibility [EN6]
2	Space utilization and flexibility (M2) Human comfort (M4) Culture (M7)	Socio-Cultural metrics group (SC-KPMs)	Functionality and Usability [SC1] Use of local materials and labour [SC2] Space utilization and usage [SC3] Architectural Considerations-cultural heritage integration and the compatibility with local heritage value [SC4] Aesthetic aspects [SC5] Indoor Environmental Quality (IEQ)- Health and Well-being [SC6] Psychological and physical comfort [SC7] Innovation and design process [SC8]
3	Cost-effectiveness (M3)	Economic metrics groups (Ec-KPMs)	Economic performance and affordability [EC 1] Building Manageability [EC2] Whole life cycle cost [EC3]
4	Working efficiency (M5) Safety and security (M6) Technological factors (M8)	Engineering and Technological Metrics Group (ETc-KPMs)	Communications and mobility [ET1] Automatics and remote control and monitoring [ET2] Fire detection and fighting [ET3] Emergency escape capability [ET4] Automatic fault detention [ET5] Possibility of further system upgrade [ET6] Compliance with regulations [ET7]

To determine the relative importance of SACs based on survey data, a ranking analysis was performed. The criteria were ranked using relative index analysis. The relative index [11] formula was used to determine the rankings.

$$RI = \sum w/A \times N \tag{1}$$

where *w*, is the weighting as assigned by each respondent on a scale of one to five with one implying the least and five the highest. *A* is the highest weight (i.e., 5 in our case) and *N* is the total number of the sample. Based on the ranking (*R*) of relative indices (*RI*), the weighted average for the groups was determined. Five important levels are transformed from Relative Index values: High (*H*) ( $0.8 \leq RI \leq 1$ ), High-Medium (*H-M*) ( $0.6 \leq RI < 0.8$ ), Medium (*M*) ( $0.4 \leq RI < 0.6$ ), Medium-Low (*M-L*) ( $0.2 \leq RI < 0.4$ ), and Low (*L*) ( $0 \leq RI < 0.2$ ). A cut-off value of 0.4 is used and the metrics as relevant for which the values are greater than or equal to 0.4. In all these, the Statistical Package for the Social Sciences (SPSS) and Microsoft Excel for

Windows application software package were employed for data analysis.

### 3. Data Analysis and Discussion

The data indicates that most respondents were employed in the private sector. The experience of the respondents was notably impressive, with 72.5% having more than 20 years of experience in the building industry. Nearly all respondents possessed considerable expertise in smart building design and construction. In terms of organizational size, 82.4% were employed in small to medium-sized organizations, while the rest worked in large organizations with over 250 employees. Furthermore, the results revealed that 91% of survey participants had completed at least undergraduate degrees, and 52% held additional postgraduate qualifications. Table 2 displays the ranking results for each sub-system, highlighting twelve performance metrics with “High” importance levels in assessing SBs, ranging from an *RI* value of 0.808 to 0.898.

**Table 2 Rank of metrics for assessing the performance of smart building systems.**

Sub-system	Key Performance Metrics (KPMs)	Valid percentage of score (%)					Relative index	Ranking by Group	Overall Ranking	Importance level
		1	2	3	4	5				
Environmental metrics group (En-KPMs)	EN1: Greenhouse Gas Emissions (GHG)	0.0	0.0	13.2	44.0	42.9	0.859	1	5	H
	EN2: Energy and Natural Resources	4.4	1.1	13.2	29.7	51.6	0.846	2	7	H
	EN3: Water conservation	1.1	7.7	29.7	38.5	23.1	0.749	4	17	M-H
	EN4: Materials used, durability, and waste	1.1	3.4	15.9	40.9	38.6	0.825	3	9	H
	EN5: Land use and site selection	4.4	15.4	31.9	37.4	11.0	0.670	6	22	M-H
	EN6: Transport and accessibility	4.4	8.8	35.2	39.6	12.1	0.692	5	21	M-H
Socio-Cultural metrics group (SC-KPMs)	SC1: Functionality and Usability	1.1	0.0	22.0	47.3	29.7	0.808	4	12	H
	SC2: Use of local materials and labour	5.5	19.8	45.1	20.9	8.8	0.615	8	24	M-H
	SC3: Space utilization and usage	1.1	10.1	36.0	34.8	18.0	0.717	6	20	M-H
	SC4: Architectural Considerations-cultural heritage integration and the compatibility with local heritage value	5.5	16.5	39.6	29.7	8.8	0.639	7	23	M-H
	SC5: Aesthetic aspects	0.0	0.0	10.1	30.3	59.6	0.898	1	1	H
	SC6: Indoor Environmental Quality (IEQ)- Health and Well being	0.0	0.0	9.9	53.8	36.3	0.853	2	6	H
Economic metrics groups (Ec-KPMs)	SC7: Psychological and physical comfort	0.0	5.5	14.3	49.5	30.8	0.810	3	11	H
	SC8: Innovation and design process	3.3	5.5	23.1	48.4	19.8	0.752	5	16	M-H
	EC1: Economic performance and affordability	3.3	8.8	19.8	39.6	28.6	0.763	2	15	M-H
	EC2: Building Manageability	3.3	2.2	22.2	38.9	33.3	0.793	1	13	M-H
	EC3: Whole life cycle cost	3.3	7.7	29.7	39.6	19.8	0.729	3	18	M-H
Engineering and Technological Metrics Group (ETc-KPMs)	ET1: Communications and mobility	0.0	0.0	3.3	47.3	49.5	0.892	1	2	H
	ET2: Automatics and remote control and monitoring	0.0	0.0	12.1	56.0	31.9	0.839	4	8	H
	ET3: Fire detection and fighting	0.0	0.0	3.2	50.4	46.2	0.886	2	3	H
	ET4: Emergency escape capability	0.0	0.0	4.4	50.5	45.1	0.881	3	4	H
	ET5: Automatic fault detention	1.1	1.1	28.6	48.4	20.9	0.774	6	14	M-H
	ET6: Possibility of further system upgrade	1.1	9.9	28.6	47.3	13.2	0.723	7	19	M-H
	ET7: Compliance with regulations	1.1	1.1	18.0	46.1	33.7	0.820	5	10	H

Twelve performance metrics were documented as having levels of importance ranging from “High-Medium”. It is noteworthy that none of these metrics were categorized as medium or lower in importance. This highlights the significance of these metrics for building designers when evaluating the performance of SBs. All metrics received ratings of either “High” or “High-Medium” importance levels.

### 3.1 Multi-attribute Assessment Model

The importance of each metric is reflected by its weight, which directly affects its contribution to the overall assessment. In this paper, the “Structure entropy weight method” is used to determine the weights. By

analyzing the system metrics and their relationships, independent hierarchies are identified. The “typical sort” of metric importance is established through a combination of Delphi experts’ investigation and fuzzy analysis method. The relative importance of metrics within the same hierarchy is obtained through data processing, resulting in metric weights that indicate their degree of importance.

Phase 1 involves acquiring experts’ opinions and establishing a typical order. Experts independently rank the assessment metrics based on their knowledge and experience. Through consultation and feedback, a consensus is reached among the experts, forming the “typical sort” of metric importance.

In Phase 2, a blind degree analysis is conducted for the typical sort. The opinions expressed in the typical sort often introduce potential deviations and uncertainties in the source data. Therefore, statistical analysis and entropy value calculation are used to qualitatively assess and process the metrics.

A set of metrics of k expert questionnaires are:  $U = \{u_1, u_2, \dots, u_n\}$ . metric collection corresponding typical sort array are:  $a_{i1}, a_{i2}, \dots, a_{in}$ . metric order matrix (typical sort) are:

$(A = (a_{ij})_{k \times n}, i = 1, 2, \dots, k, j = 1, 2, \dots, n)$ .  $a_{ij}$  is the assessment  $u_j$  of expert i to indicator j.

Quantitative transformation for typical sort, membership function definition:

$$\mu(I) = -\frac{\ln(m - I)}{\ln(m - 1)} \tag{2}$$

$I$  is a qualitative sequence number for the evaluation of each metric according to the form of typical sort by experts.  $\mu(I)$  is the membership function value corresponding  $I$ .

$I = 1, 2, \dots, j, j+1, j$  is the actual maximum sequence number, that is serial number of metric.  $m$  is transformation parameter number,  $m = j + 2$ .

$I = a_{ij}$  is substituted into formula(1), quantitative transformation value of  $a_{ij}$  is  $b_{ij}$  ( $\mu(a_{ij}) = b_{ij}$ ),  $b_{ij}$  is the membership of sequence number. Matrix  $B = (b_{ij})_{k \times n}$  is membership matrix. It is the consistent view of  $u_j$  by k experts. Mark it as  $b_j$ ,

$$b_j = (b_{1j} + b_{2j} + \dots + b_{kj})/k \tag{3}$$

Uncertainty caused by acknowledges of expert  $z_i$  on  $u_j$  is defined, called blind degree  $Q_j$ ,

$$Q_j = \frac{1}{2} [|\max(b_{1j}, b_{2j}, \dots, b_{kj}) - b_j| + |\min(b_{1j}, b_{2j}, \dots, b_{kj}) - b_j|] \tag{4}$$

General understanding degree of k experts about  $u_j$  is defined, marked as  $x_j$ ,

$$x_j = b_j (1 - Q_j), x_j > 0 \tag{5}$$

The evaluation vector of the entire metrics  $u_j$ :  $X = (x_1, x_2, \dots, x_n)$ .

Phase 3: normalized processing

In order to obtain the weight of the metric  $u_j$ ,  $x_j = b_j (1 - Q_j)$  is normalized, set:

$$a_j = \frac{x_j}{\sum_{i=1}^m x_j} \tag{6}$$

$(a_1, a_2, \dots, a_n)$  is the consistency judgment for importance of factor sets  $U = \{u_1, u_2, \dots, u_n\}$  by k experts.  $W = \{\alpha_1, \alpha_2, \dots, \alpha_n\}$  is the weight vector of factor set  $U = \{u_1, u_2, \dots, u_n\}$ .

Fuzzy comprehensive evaluation use fuzzy transform principle and maximum membership degree to make a comprehensive evaluation, considering the various factors related to evaluate things. Fuzzy mathematical make fuzzy things enter into mathematical model without cutting, and finally make segmentation on a proper threshold value by making full use of intermediary information. It can also reduce influence of subjective factors and make the result of the evaluation more objective and reliable.

The influence factors of smart buildings are  $U = \{u_1, u_2, \dots, u_n\}$ ,  $u_1, u_2, \dots, u_n$  are assessment metrics. Valuation level are  $V = \{v_1, v_2, v_3\}$ . Metric weight vectors are:  $W = \{\alpha_1, \alpha_2, \dots, \alpha_n\}$ . The fuzzy set  $(r_{i1}, r_{i2}, \dots, r_{im})$  are fuzzy mapping from  $U$  to  $V$ :  $U \rightarrow V$ , which identify a judgment matrix:  $R = (r_{ij})_{n \times m}$ . The single factor evaluation result is  $B = W \cdot R$ . Comprehensive evaluation model:  $C = W \cdot B = W \cdot (b_{ij})_{n \times m}$ . Vector  $C$  determines evaluation results by max membership degree principle.

#### 4. Conclusions

Research was conducted to determine performance assessment metrics for smart building systems by reviewing relevant literature and considering the features of smart buildings. A questionnaire survey was utilized to gauge the perceived significance of these metrics. Subsequently, twenty-four performance metrics were identified as crucial components of smart building systems based on the survey results. The theoretical foundation for the design and evaluation of smart buildings is established through eight “quality environment modules” (QEMs). An assessment model is proposed using an analytic hierarchy process and multi-level fuzzy analysis technique.

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