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FUNDAMENTALS OF DEVELOPING CONCEPTUAL COST ESTIMATION MODELS USING MACHINE LEARNING TECHNIQUES: SELECTION AND MEASUREMENT OF BUILDING ATTRIBUTES

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Abstract

Ensuring the identification of building attributes is the primary task in developing a machine learning cost estimation model. However, the existing research on building attributes has the following shortcomings: it struggles to categorize building characteristics according to various cost types, and the suggested sets of attributes do not clearly establish measurement standards for these qualities. To address these issues, this study aims to select a set of building attributes suitable for conceptual cost estimation and establishment of measurement standards. Through a two-round process of focused group discussions, this research ultimately identified 13 building attributes that can be collected before the completion of building design. These attributes serve as a basis for assessing completed building projects during the model development phase and for evaluating new projects during the model application phase. This study provides a foundational framework for the development of conceptual cost estimation models, ultimately enhancing the accuracy of machine learning cost estimation models.

***Keywords**: Conceptual cost estimation, machine learning, building attributes*

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INTRODUCTION

The success of construction projects is heavily dependent on cost prediction (Juszczyk, 2020; Park et al., 2022; B. Wang et al., 2021). A successful construction project should achieve on-time delivery within the budget while yielding a substantial return on investment (Ma et al., 2016; Peleskei et al., 2015). Inaccurate estimations can lead to cost overruns, construction delays, and many other, even worse, outcomes (Car-Puši & Mladen, 2020; Elmousalami, 2020; Mir et al., 2021).

Currently, qualitative and quantitative analyses are the primary methods for cost estimation (Hashemi et al., 2020). Qualitative methods based on expert judgment may introduce biases and result in inaccurate estimates (R. Wang et al., 2022). Quantitative techniques not only rely on historical data and expert knowledge but can also analyze project design, processes, and unique characteristics (Ugur, 2017). Quantity surveying is considered the most reliable quantitative method for obtaining construction costs (Ugur et al., 2018). However, it requires surveyors to possess substantial expertise, can be time-consuming, and is only feasible with a well-developed design (Ugur et al., 2018). Therefore, there is a need to enhance the efficiency of quantity surveying. Other traditional quantitative cost estimation methods mostly depend on statistical analysis and simple regression theory, which results in lower accuracy and longer time consumption and does not add value to cost estimation (Jiang, 2019). As a result, traditional budgeting methods no longer meet the needs of practical engineering budgets. It is essential to use computer technology for intelligent cost control in construction budgeting to improve accuracy (Abdel-Basset et al., 2020; Patil & Salunkhe, 2020; Xuan & Li, 2022).

Machine Learning (ML) is a branch of Artificial Intelligence (AI) and is a data-driven modelling technique (Brink et al., 2016). It can be used to automatically extract hidden patterns from high-dimensional data and convert them into explicit information or knowledge to address challenging issues in the construction industry (Zhou et al., 2018). As the name suggests, using ML methods to predict construction costs can eliminate the need for experts and quantity surveying calculations (Ugur et al., 2018) and can also overcome the issue of lacking accurate estimation data at the project's outset (Saeidlou & Ghadiminia, 2023).

Identifying building attributes is a primary task in developing machine learning cost estimation models. However, as summarized through the literature review, there is a lack of comprehensive research on the standardized selection of attributes for machine learning models in the field of construction cost estimation (Elmousalami, 2020; Pike & Grosse, 2018). To address this gap, Salleh et al. (2023) conducted a study to establish a standardized set of building attributes to guide the development of construction cost estimation models.

Nevertheless, the attribute set still has the following shortcomings: 1) The study only identified the importance of different attributes but did not categorize attributes based on the needs of different cost types, such as conceptual cost estimation before design completion and project cost estimation after design completion; 2) The established attribute set did not provide clear measurement standards for attributes, including the classification and interpretation of numeric and textual attributes.

Therefore, to effectively address these issues, this study aims to select a set of building attributes suitable for conceptual cost estimation and establishment of measurement standards. This research, using a focused group discussion methodology, builds upon the standard building attribute set proposed by Salleh et al. (2023). It selects attributes that can be obtained before the building design is completed and provides clear measurement standards for these attributes. This study lays the foundation for developing construction conceptual cost estimation models, enhancing accuracy.

LITERATURE REVIEW

The main process of developing a machine learning cost estimation model

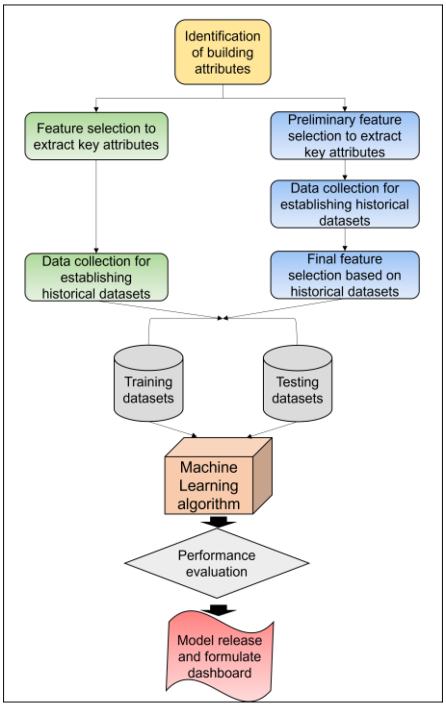

Figure 1: Flowchart for developing machine learning cost estimation model
Source: compiled from (Abed et al., 2022; Hashemi et al., 2020)

Figure 1 illustrates the main process of developing a machine learning cost estimation model. Initially, the identification of building attributes was the first task in the development of the model. Subsequently, key attributes were extracted from the identified building attributes. Then, data collection was conducted based on these key attributes to create a completed project dataset. This preparation is critical because the accuracy of the cost estimation model is affected by the input building attributes and the size of the dataset (Cho et al., 2013). In terms of feature selection, the dual feature selection method (blue area) is considered more scientific than the traditional method (green area). Prior to data collection, attribute importance is usually determined based on expert judgment and subjective ratings. However, dual feature selection ensures that the importance of attributes is assessed based on historical data after data collection is complete, and quantitative methods such as regression analysis are used (Matel et al., 2022). Once the data collection and identification of key attributes are complete, the historical dataset is divided into training and test sets and fed into the machine learning algorithm. To effectively validate the performance of the developed models, it is a prerequisite that various performance evaluation methods are used and multiple models are tested.

Therefore, identification of building attributes, feature selection, collection of completed project datasets, optimisation of machine learning algorithms, and evaluation metrics for model performance are key steps in the development of machine learning cost estimation models for construction projects (Abed et al., 2022; Hashemi et al., 2020). These steps contribute to improving the accuracy of cost estimation in construction projects, thereby enhancing project management efficiency and decision-making accuracy.

Building attribute datasets

In the context of construction cost estimation, attributes refer to specific features or factors considered in the estimation process to determine the construction cost of a building or structure (Elhag & Boussabaine, 1998; Elmousalami, 2020). Having a sufficient number of building attributes and a larger dataset of completed projects can effectively enhance the accuracy of cost estimation (Shin, 2015; Y.-R. Wang et al., 2012). The accuracy of cost estimation models can vary based on the input building attributes (Cho et al., 2013). However, it is not feasible to incorporate every possible attribute that a building might have into an estimation model (Juszczyk, 2017), and the selection of building attributes requires further research (B. Wang et al., 2021).

From the authors' previous study, Salleh et al. (2023) initially conducted a literature review to summarize a significant number of attributes. Then, through a questionnaire survey and focused group discussions during the Delphi research phase, they eventually identified 68 ranked attributes and formulated a building data attribute set, which includes 12 categories of variables such as Project Strategic and Parties-involved (as shown in Figure 2). This study provides the essence for the development of machine learning models for construction cost estimation, and future researchers in the field can refer to these listed attributes to determine the layout structure of new models. However, the attribute set still has the following shortcomings:

- The study only determined the importance of different attributes but did not categorize attributes based on the needs of different cost types, such as conceptual cost estimation before design completion and project cost estimation after design completion.
- The established attribute set did not provide clear measurement standards for attributes, including the classification and interpretation of numeric and textual attributes.

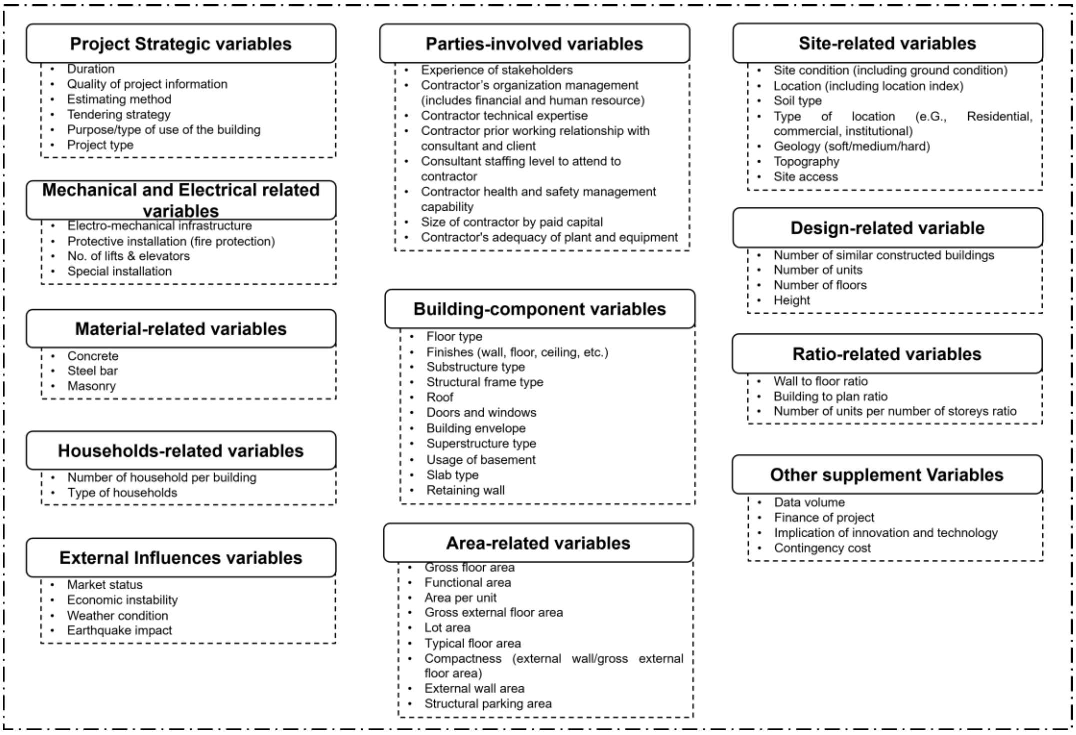

Figure 2: A standard attribute set of building for cost estimation
Source: summarized from (Salleh et al., 2023)

RESEARCH METHODOLOGY

The application of the focus group discussion in this research is to poll a group of experts to reach a group consensus regarding the classification of attributes in building cost estimation. The focus group discussion was conducted in October 2023 in the Faculty of Built Environment, University of Malaya and mainly includes two rounds (refer to Figure 3): selecting building attributes for which data will be available before the building design is completed; clarifying the measurement of different attributes, both numeric and text. As the measurement of building attributes varies from country to country, three overseas experts were also invited for this study, the 14 experts of this study are shown in Table 1.

Table 1: Expert panel list of the focus group discussion

Experts	Age	Gender	Position	Working Experience	Country
E1	33	Male	Construction technical staff	8 years (Enterprise)	Malaysia
E2	41	Female	Construction technical staff	14 years (Enterprise)	Malaysia
E3	32	Male	Construction technical staff	6 years (Enterprise)	China
E4	38	Male	Researcher in quantity surveying	9 years (Institute)	England
E5	31	Female	Researcher in quantity surveying	7 years (Institute)	Malaysia
E6	42	Male	Researcher in quantity surveying	7 years (Institute)	Malaysia
E7	36	Female	Researcher in quantity surveying	6 years (Institute)	Malaysia
E8	35	Female	Researcher in quantity surveying	4 years (Institute)	Malaysia
E9	44	Male	Manager of building cost services	10 years (Enterprise)	Malaysia
E10	51	Male	Manager of building cost services	14 years (Enterprise)	Malaysia
E11	38	Female	Manager of building cost services	8 years (Enterprise)	Malaysia
E12	36	Female	Cost estimator	6 years (Enterprise)	Malaysia
E13	47	Male	Cost estimator	14 years (Enterprise)	China
E14	44	Male	Cost estimator	9 years (Enterprise)	Malaysia

Source: from the actual focus group discussion

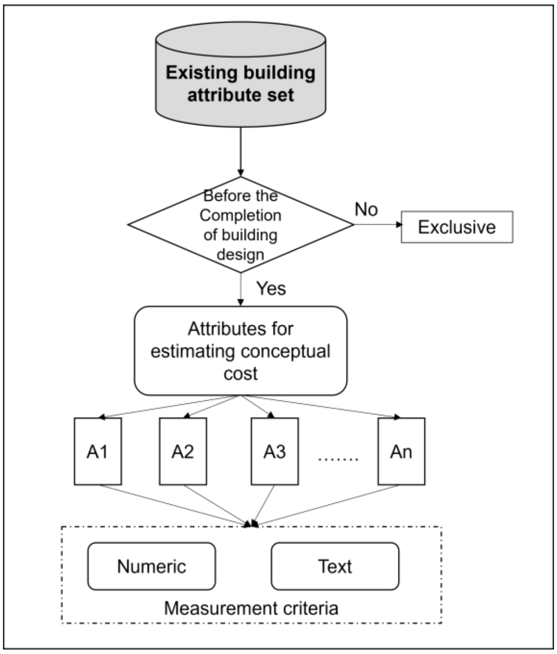

Figure 3: Research flowchart of focus group discussion
Source: Authors' Deliberation

Round 1: Selecting building attributes for conceptual cost estimation
Based on a literature review and the existing attribute sets, the attributes were categorized with respect to the completion of the building design as the boundary. In focused group discussions, experts were surveyed using a questionnaire to select attributes based on their past experiences. The goal was to determine which subset of attributes could be used to estimate conceptual costs by collecting data before the completion of building design. The final selection of attributes was made based on the results summarized from the questionnaires.

Round 2: Clarifying the measurement of different attributes
In the second round of discussions, experts provided their opinions on how to measure different attributes. In this study, expert viewpoints were aggregated and categorized. Based on the expert perspectives, specific measurement criteria for each attribute were summarized, and a distinction was made between numeric and textual attributes.

RESULT AND DISCUSSION

Selected building attributes for conceptual cost estimation

In the discussion, all experts unanimously agree that Duration, Number of Floors, Building Height, Floor Area, Tendering Strategy, Project Type, Type of Use of the Building, Soil Type, Topography, and Location can be considered as attributes for conceptual cost estimation. This is because these attributes can provide data at the preliminary design stage. However, there is controversy regarding the following 3 attributes:

- Market Status: Experts E5, E6 and E14 believe that measuring this attribute during the model application stage is challenging. Understanding future market conditions requires predicting trends based on past economic development, which demands a high level of economic knowledge. Considering the practical application of the model, if the relevant business has good market forecasting capabilities and can accurately predict future indicators such as inflation and lending rates, this attribute may be used as an input variable for the predictive model.

- Weather/Earthquake Impact: Expert E7 and E10 consider both of these attributes as uncertain factors. Although they can significantly impact project costs, they are challenging to measure. For example, different magnitudes of earthquakes can have varying impacts, but it is impossible to predict the magnitude of future earthquakes when applying the model. Weather impacts include seasons such as rainy or snowy periods, but these attributes cannot be quantified. Therefore, for these two attributes, if the project location for the model application is in an earthquake-prone or weather-affected area, these attributes may be considered; otherwise, they may not be relevant.

Through the first round of data collection from the questionnaire as well as data analysis, 13 building attributes that could be used to obtain data before the completion of the building design were screened and the results are shown in Table 2.

Table 2: Attributes for estimating conceptual cost

Classification	Attributes
Compulsory	
Project Strategic variables	Duration
	Tendering strategy
	Type of use of the building
	Project type
Area-related variables	Floor area
Site-related variables	Location
	Soil type
	Topography
	Number of floors
	Height
Alternative	
External influence variables	Market status
	Weather impact
	Earthquake impact

Source: from research result

Measurement of different attributes

In the second round of discussion, the author first introduced the regular measurement methods for 13 screened attributes, then the experts proposed recommendations based on personal experience. For most attributes, experts generally agree with the author's proposed measurement criteria. However, some experts have suggested additional considerations.

- E2 and E6 believe that when measuring the number of floors, it is essential not only to consider the total but also to differentiate between above-ground and below-ground floors. The costs between these two types of floors can vary significantly in actual construction and should be measured separately.

- E5, E6, and E14 recommend that when assessing market status, careful consideration should be given to changes in exchange rates and inflation. These factors directly impact material and labour costs, potentially causing fluctuations in project costs. Additionally, financing costs, contract agreements, and project timelines are also influenced by these changes and must be thoroughly considered in cost estimation to ensure accuracy and project control.

- E13, an expert from China, suggests dividing the Location attribute into two levels for measurement. Firstly, considering the differences in consumption levels in different cities, it is divided into various levels in the first tier. In the second tier, the expert further specifies the building's location based on differences between the city centre and suburbs. Therefore, a more detailed division of the building location helps more accurately capture the unique cost factors in the project's region, enhancing the accuracy and reliability of cost estimation.

All in all, the metrics are adapted to the measurement of historic buildings in the model development phase and the measurement of new projects in the model application phase, as shown in Table 3-4. It is important that the proposed metrics be adapted to the specific conditions of different countries. Table 3 describes the standards that can be measured numerically and Table 4 shows the standards that can be measured using text categorization.

DISCUSSION

In the two phases of our investigation, we delved into the identification of building attributes for their utility in conceptual cost estimation and the establishment of measurement criteria for these attributes. By actively engaging experts in the field, we were able to refine the selection of relevant attributes and define precise measurement guidelines. This comprehensive approach has significantly enhanced the accuracy and reproducibility of cost estimates.

The implications of our research extend to the realms of cost control and forecasting, offering valuable insights for both project planning and decision-making processes. The meticulous extraction of applicable building attributes and the elucidation of specific measurement criteria contribute to a more robust foundation for cost estimation methodologies. This newfound clarity not only aids in improving the overall reliability of cost estimates but also facilitates a more systematic and informed approach to decision-making throughout various stages of project development.

The significance of our findings becomes particularly evident in their potential impact on the advancement of machine learning (ML) models for conceptual cost estimation. The precisely identified attributes and their measurement criteria serve as crucial groundwork, laying the foundation for the future development of innovative ML models. These models have the potential to further refine and automate the conceptual cost estimation process, offering a promising avenue for continued advancements in the field of construction project management.

Table 3: The measurement of numeric attributes

Attributes	Specification	Measurement
Duration	Time of construction	Monthly-based
Number of the floor	On the ground	Quantities
	Under the ground	Quantities
Building height	Height from roof deck to outdoor floor level	Metre-based
Floor area	The footprint of the building	Square metre
Total floor area	Total area of the building	Square metre
Market status	Inflation rate	(%)
	Lending rate	(%)

Source: from research result

CONCLUSION

In the development of machine learning cost estimation models, the currently proposed building attribute sets have the following shortcomings: they do not classify building attributes based on the needs of different cost types, and they do not provide clear measurement standards for these attributes. Therefore, this study aims to address these issues using a two-round, focused group discussion approach to select a set of building attributes suitable for conceptual cost estimation and establish measurement standards. The study ultimately identified 13 building attributes that can be obtained before the completion of building design. These attributes are used for assessing completed buildings during the model development phase and for evaluating new projects during the model application phase. This research provides a foundational framework for the development of construction conceptual cost estimation models, thereby enhancing the accuracy of machine learning cost estimation models.

While this study has successfully addressed the deficiencies in existing machine learning cost estimation models by identifying a set of building attributes for conceptual cost estimation and establishing clear measurement standards, it is essential to acknowledge its limitations. One notable limitation is the exclusive focus on attributes relevant to conceptual cost estimation, without delving into the intricacies of cost estimation beyond the completion of the design phase. Future research endeavours should aim to bridge this gap by conducting more in-depth investigations into the attributes influencing cost estimates in the post-design stages. This comprehensive approach would provide a more holistic understanding of the factors impacting construction project costs throughout the entire lifecycle. Looking ahead, researchers should consider extending their focus to include attributes specific to post-design stages, facilitating a more comprehensive cost estimation model. This expansion could encompass factors such as construction materials, labour costs, and technological advancements that play a pivotal role in determining project costs beyond the conceptual phase.

Table 4: The measurement of text attributes

Attributes	Measurement			
Tendering strategy	Open tendering	Invitation to tender	Negotiation	Competitive negotiation
	( )	( )	( )	( )
Project type	New Construction	Alterations	Extensions	
	( )	( )	( )	
Type of use of the building	Residential	Office	Commercial	Industrial
	( )	( )	( )	( )
Location 1	First Tier Cities	New Tier 1 Cities	Second-tier cities	Third-tier cities
	( )	( )	( )	( )
	Fourth-tier cities	Fifth-tier cities		
	( )	( )		
Location 2	City centre	Outskirts		
	( )	( )		
Soil type	Sand	Clay	Rock	
	( )	( )	( )	
Topography	Flat	Hillside	Mountain	
	( )	( )	( )	
Weather impact (Severe weather prone areas)	Rainstorms	Snowstorms	Windstorms	None
	( )	( )	( )	( )
Earthquake impact	Seismic zone	Non-seismic zone		
	( )	( )		

Source: from research result

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