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Fuzzy AHP Approach for Enhancing Excavation Support System Selection in Building Projects: Balancing Safety and Cost-Effectiveness

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Abstract: Selecting the appropriate excavation support system (ESS) is critical for ensuring construction projects' safety and cost-effectiveness. Several dynamic factors influence this decision-making process, such as the groundwater table, excavation depth, proximity to neighboring buildings, and soil characteristics. In practice, the selection often depends heavily on the subjective judgment of experienced professionals in the construction industry. Although the analytical hierarchy process (AHP) is frequently employed to evaluate alternatives using multiple criteria, it fails to adequately account for the subjectivity and uncertainty in converting the decision-maker's intuition into exact numerical values. To overcome this challenge, this study proposes an enhanced method known as fuzzy AHP. This approach is designed to capture the subjective experiences of experts better and effectively incorporate the uncertainties present in the decision-making process, ultimately aiding in identifying the most suitable ESS. A case study of excavation projects is also included to demonstrate the practical application of the proposed model. By presenting this approach, the study aims to raise awareness within the construction industry about the critical factors to consider when selecting the best excavation support technique for specific projects.

Keywords: excavation support system; fuzzy logic; AHP; multiple criteria evaluation; construction industry

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1. Introduction

1.1. Background and Key Challenges

Excavation plays a crucial role in various construction endeavors, ranging from the creation of building foundations to the development of underground infrastructure. These projects' safety and overall success rely heavily on the proper use of effective Excavation Support Systems (ESSs) (Ghorbani et al., 2012; Liu et al., 2016 [1,2]). These systems are essential for preserving soil stability, safeguarding workers, and protecting nearby structures during excavation [3].

The use of ESSs is especially crucial in the construction sector for several key reasons. First, ESSs are designed to prevent the collapse of soil walls, reducing the risk of dangerous cave-ins and ensuring a safe work environment for construction workers. Second, these systems help protect nearby structures, utilities, and infrastructure by preventing potential damage caused by uncontrolled soil movements during excavation. Ultimately, ESSs promote the smooth and timely progress of projects by providing a stable base for the subsequent construction phases. Maintaining the excavation site's integrity allows construction teams to work efficiently, meet deadlines, and uphold safety standards [4].

Although excavation activities are essential, they come with inherent risks and challenges that need to be carefully managed. Issues like soil instability, fluctuating water tables, and the closeness of existing structures can create dangerous conditions if not adequately addressed. Accidents during excavation can lead to injuries, delays, and finances [5,6]. Consequently, it is vital to deploy effective ESSs that can help mitigate these risks.

Selecting the right ESS requires thoroughly assessing several key factors. The type and condition of the soil, excavation depth, groundwater table level, and nearby structures all significantly impact the choice of the most appropriate support system [7]. Additionally, the water table's effect on soil stability and the project's duration must be carefully considered [8]. The following subsections provide a brief overview of the importance of these factors:

Initially, soil type is a key factor in determining the design of ESSs. Different soil types exhibit varying characteristics, such as cohesion, internal friction, and effective density, all influencing the choice of appropriate support methods. Systems such as soldier piles with lagging or diaphragm walls are often preferred for cohesive soils like clay. In contrast, granular soils like sand may require different support systems, such as sheet piles [3]. The soil type also plays a critical role in determining both the stability of the excavation and the risk of ground settlement, making it a crucial factor in the design and safety of ESSs [9].

Secondly, excavation depth is a fundamental factor in designing ESSs. The depth directly influences the complexity and type of support system needed. More robust support is required for deeper excavations, such as soldier piles and sheet piles, or stronger systems like concrete secant piles or diaphragm walls. This enhanced support is crucial to prevent soil movement, subsidence, and ground heave. The selection of the appropriate support system depends on factors such as soil characteristics, expected loads, and safety standards, requiring customized solutions that align with the excavation depth [10].

The third critical factor is the groundwater table level, which directly affects excavation stability. A high groundwater table increases the risk of water seepage and instability, including uplift and piping. As a result, dewatering techniques are crucial to lowering the water table and ensuring a safe working environment. The success of dewatering methods, such as well points or deep wells, depends on the groundwater level. Effective management of these techniques is vital to prevent flooding and protect construction workers. Additionally, the groundwater table creates extra lateral pressure on the shoring system, making it necessary to choose a watertight system to prevent leakage [11].

Lastly, the proximity of adjacent buildings to the excavation site adds another layer of complexity. Excavation activities can lead to ground settlement, which may threaten the structural integrity of nearby buildings. Ensuring the stability and safety of these surrounding structures is crucial, requiring underpinning methods, structural reinforcement, and controlled excavation techniques to minimize the impact on neighboring buildings [6].

Deep excavation projects present significant challenges in ensuring safety and quality, as unstable soil conditions, groundwater infiltration, and proximity to adjacent structures can lead to catastrophic failures if not properly managed [2]. Selecting an appropriate ESS is a critical decision that directly impacts worker safety, structural integrity, and project success. Traditional selection methods often rely on subjective experience or simplified technical assessments, which may fail to account for uncertainties in soil behavior, dynamic site conditions, or evolving safety regulations [7]. Safety considerations such as preventing soil collapse, minimizing vibrations, and protecting nearby infrastructure must balance quality requirements, including long-term durability, water tightness, and compliance with engineering standards [4]. For instance, diaphragm walls offer high rigidity and water resistance but may be cost-prohibitive, while soldier piles are economical but less practical in high-water-table conditions [12]. These trade-offs complicate the selection process, necessitating a systematic approach integrating multi-criteria decision-making (MCDM) with real-world constraints.

In conclusion, a comprehensive understanding of the collective influence of these factors ensures safety, cost optimization, and minimizes environmental impact on construction projects. The meticulous consideration and integration of soil type, excavation depth, groundwater table level, and proximity to adjacent structures collectively contribute to the practical design and implementation of ESSs in construction endeavors.

1.2. Overview of Excavation Support Systems and Decision-Making Methods

Table 1 presents a detailed comparison of different ESS techniques used in building projects, including a concise overview of each method's mechanism, benefits, and drawbacks. In summary, diaphragm wall shoring provides strong structural support and is watertight but can be complex and expensive. Secant piles are versatile, though not as rigid or watertight as diaphragm walls. Steel sheet pile shoring is a cost-effective solution for temporary excavations but may cause noise and vibration and may not offer the same level of watertightness as other systems. Lastly, soldier pile shoring provides a quick and affordable option for dry, temporary, shallow excavations.

Table 1. Widely used excavation support systems.

Feature	Description	Suitability	Advantages	Disadvantages	References
Diaphragm Wall	Reinforced concrete wall constructed using slurry trench excavation	- Deep excavations - Unstable soil - High water table	- High strength and stiffness - Any depth - Watertight	- Time-consuming - Expensive - Needs specialized equipment	[11,13]
Steel Sheet Pile	Thin, interlocked steel walls driven into the ground.	- Shallow to deep excavations - Stable soil - Low water table	- Easy installation and removal - Reusable - Suitable for limited spaces	- Difficult in hard soil/rock - Susceptible to corrosion	[1,14]
Secant Piles	Overlapping reinforced concrete piles form a continuous wall.	- Deep excavations - Unstable soil - High water table	- High strength and stiffness - Any depth - Watertight	- Time-consuming - Expensive - Needs specialized equipment	[15,16]
Soldier Pile Shoring	Vertical steel I- or H-beams with horizontal lagging.	- Shallow to deep excavations - Stable soil - Low water table	- Cost-effective - Easy installation - Suitable for limited spaces	- Lower strength/stiffness - Not ideal for high water tables	[17]

The literature contains numerous MCDM applications within civil engineering projects (CEPs), particularly in construction and geotechnical engineering. For instance, ref. [18] integrated a framework combining Building Information Modeling (BIM) and multi-objective optimization to enhance decision-making in deep excavation projects. The proposed model optimizes cost, duration, safety, and environmental impact by incorporating the critical path method, system reliability, reward-penalty mechanisms, and environmental assessments. An improved Multi-Objective Particle Swarm Optimization (MOPSO) algorithm is introduced. The research highlights the potential of BIM-driven optimization to improve efficiency and sustainability in construction projects. Lin et al. [19] described an MCDM-based approach using TOPSIS to identify high-risk factors in excavation construction. The study developed an expert coefficient to evaluate the significance of expert judgments and categorized risk factors into geotechnical conditions, surrounding environment, construction measures, and management. Spherical and triangular fuzzy sets were employed to handle uncertainties in expert judgments and measured data. Issa et al. [20] presented a hybrid AHP-Fuzzy TOPSIS method for choosing the most appropriate deep excavation support system (DESS) in construction projects. An MCDM model, integrated with expert knowledge, cost, and soil property data, is developed to address the complexity and uncertainty inherent in such decisions. The results indicated that secant pile walls were the most preferred option, followed by sheet pile walls and soldier piles with lagging. Shahpari et al. [21] combined the Delphi method, analytic network process (ANP), and decision-making trial and evaluation laboratory (DEMATEL) with the technique for order of preference by similarity to the ideal solution (TOPSIS) to create a tool for assessing the efficiency of residential building construction systems. Similarly, this study aims to raise awareness within the construction industry by highlighting the crucial factors to consider when selecting the most suitable excavation support method for specific projects. In another study, Temiz and Calis [14] applied the preference ranking organization method alongside the analytical hierarchy process (AHP) to determine the most suitable excavation equipment for a construction site. Similarly, Penadés-Plà et al. [22] employed AHP to prioritize durable and sustainable solutions in the design of a continuous concrete box-girder pedestrian bridge deck. Furthermore, in the context of excavation project selection techniques, Qi et al. [23] utilized the analytical hierarchy process (AHP) in combination with the Delphi technique to determine appropriate protection methods for underground excavation and deep excavation construction techniques in building projects.

The foundation of these decision-making approaches can be traced back to Saaty [24], who introduced AHP as a structured technique for ranking the relative importance of different solutions to MCDM challenges. AHP facilitates decision-making by integrating both quantitative criteria and qualitative assessments [25]. Meanwhile, alternative approaches such as fuzzy TOPSIS address uncertainties by utilizing linguistic variables instead of precise numerical values, making them effective for handling incomplete or ambiguous data [26]. Furthermore, triangular fuzzy numbers (TFNs) have gained prominence in CEPs due to their computational simplicity and ability to enhance information processing in fuzzy environments [27]. TFNs have proven particularly effective in modeling decision-making problems where subjective and imprecise information plays a critical role.

1.3. Study Context, Research Gap, and Objectives

The selection of ESSs in building projects is a complex task, particularly in regions with challenging geotechnical and operational conditions. In Egypt, construction projects frequently encounter unique site constraints such as prevalent sandy soils, high groundwater tables, and densely built urban environments. These factors introduce significant uncertainty and risk, making the decision process highly sensitive to local context and expert judgment.

Despite the critical importance of ESS selection, most previous studies have either focused on generic criteria or applied MCDM methods that inadequately address the inherent subjectivity and ambiguity in expert assessments. Traditional AHP, while widely used, requires precise numerical judgments, which may not realistically reflect the uncertainty and linguistic nature of expert opinions in real-world excavation projects. Furthermore, the literature reveals a lack of comprehensive frameworks tailored to the specific geotechnical challenges and construction practices in Egypt.

To address these gaps, this study applies fuzzy AHP to the selection of ESSs within the Egyptian construction context. By integrating fuzzy logic with AHP, the proposed approach enables the use of linguistic variables and triangular fuzzy numbers, thus more accurately capturing the uncertainties and subjectivities inherent in expert decision-making. This enhances the robustness and reliability of the selection process. The main objectives of this study are as follows:

- To develop a context-specific, MCDM framework for ESS selection that incorporates the unique geotechnical and operational challenges of building construction in Egypt.
- To demonstrate the effectiveness of the fuzzy AHP approach in capturing expert judgment uncertainty and improving the prioritization of selection criteria and alternatives.
- To validate the proposed framework through a real-world case study, thereby illustrating its practical applicability and value for construction practitioners.

By addressing these objectives, the study fills a critical gap in the literature and provides a practical, adaptable tool for enhancing safety and cost in ESS selection for building projects in Egypt and similar contexts.

2. Research Methodology and Model Development

A structured framework for prioritizing the optimal deep excavation supporting system is developed using the fuzzy AHP approach. The implementation of this model is visually depicted in Figure 1. The proposed integrated fuzzy model is constructed within the AHP framework, incorporating refinements to Pan's model [28]. The methodology follows a systematic process consisting of several key steps: (1) establishing a hierarchical structure, (2) conducting fuzzy pairwise comparisons, (3) performing consistency checks, (4) computing relative weights, and (5) synthesizing group decisions. The subsequent sections comprehensively explain each component within the proposed fuzzy AHP model.

2.1. Development of the Decision Hierarchy

The analytic hierarchy process (AHP) involves a structured series of steps to support decision-making. First, the decision problem is defined, and a goal is established. Then, a hierarchical model is built, comprising the overall goal, evaluation criteria (and sub-criteria if needed), and the set of alternatives. Next, pairwise comparisons are performed between criteria and alternatives, often using Saaty's scale or fuzzy extensions, to assess their relative importance. The relative weights (priority vectors) are calculated from these comparisons, typically using the geometric mean method. Consistency of judgments is then checked by calculating the consistency index (CI) and consistency ratio (CR), with an acceptable CR generally below 0.10. After ensuring consistency, the local weights are synthesized across the hierarchy to determine the global priorities of the alternatives. Finally, the best option is the alternative with the highest priority score.

2.2. Fuzzy Pairwise Comparisons

In general, a fuzzy AHP decision problem comprises the following key components: (1) a set of alternative options M_i $(i = 1, 2, \ldots, m)$; (2) a collection of evaluation criteria C_j $(j = 1, 2, \ldots, n)$; (3) a linguistic judgment $_{ij}$ representing the relative importance of each pair of criteria; and (4) a weighting vector, $w = (w_1, w_2, \ldots, w_n)$. Pairwise comparisons are used in the evaluation process after establishing the hierarchy. Each criterion from the previous upper level is systematically compared with all criteria at the same hierarchical level. Decision-makers use linguistic phrases to make pairwise comparisons. The reciprocal comparisons of criteria at the same level, or of all potential alternatives, generate the resulting matrices used to compare the criteria or alternatives.

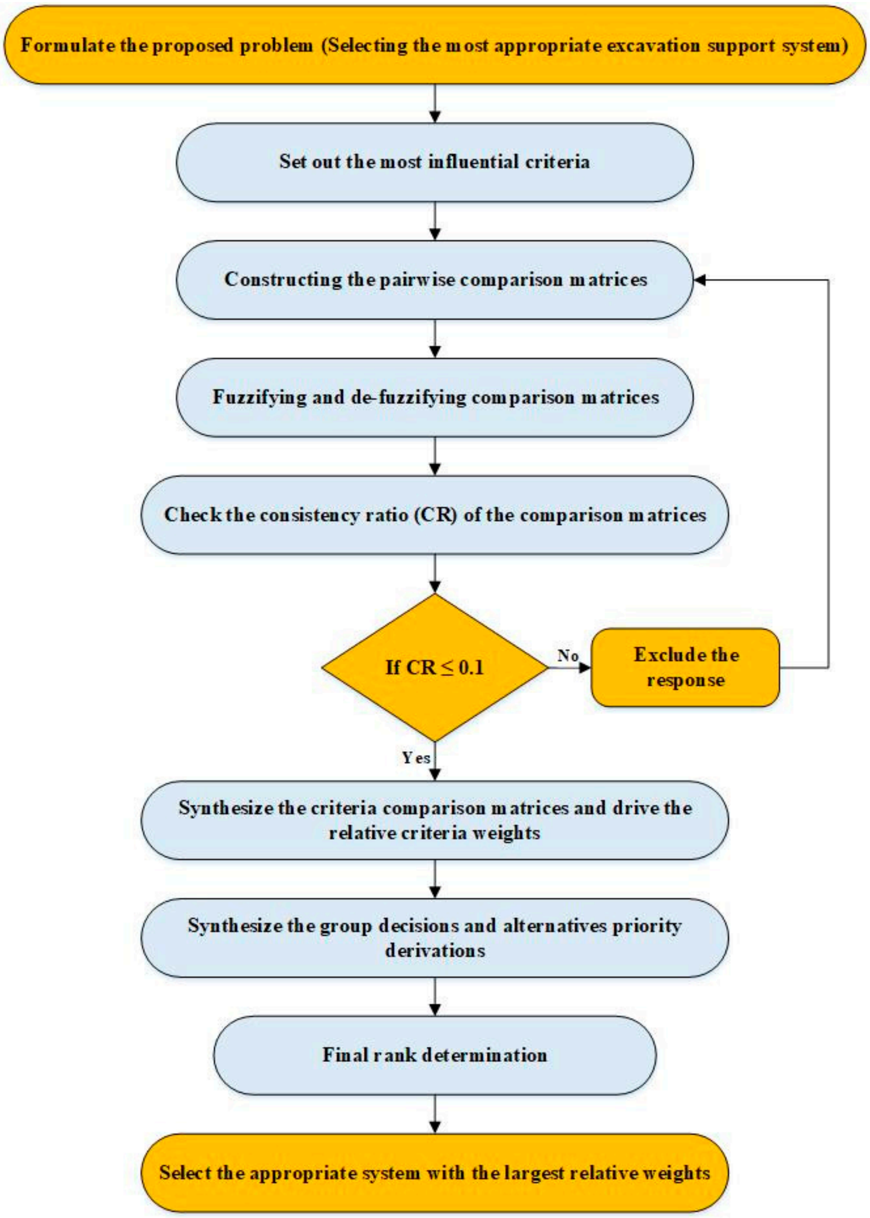

Figure 1. The proposed Fuzzy–AHP model diagram.

This study separates the evaluation process into two stages because of the large number of criteria and options and the unique and varied character of projects. Common factors impacting the choice of a suitable ESS are assessed in the first phase. This entails assembling a panel of decision-makers from the building industry. Following that, the project decision team determines and evaluates potential options in accordance with the predetermined standards. Acknowledging the subjectivity and ambiguity that come with determining significance through pairwise comparisons, this method uses a symmetric triangular membership function to accommodate triangular fuzzy numbers. A linguistic variable is a type of variable where the values are represented using linguistic terms. In this study's pairwise comparison process, five linguistic terms are defined: "Very Unimportant" (VU), "Less Important" (LI), "Equally Important" (EI), "More Important" (MI), and "Very Important" (VI). These terms are assigned numerical values ranging from 1 to 5, respectively, as detailed in Table 2. A fuzzy number or linguistic variable can be represented by a membership function, $\mu_A(x)$, as shown in Figure 2. This study employs a fuzzy importance scale for pairwise comparisons, assigning fuzzy numbers to different levels of verbal judgment. The scale consists of five linguistic terms, each representing a distinct level of importance:

Table 2. Fuzzy importance scale.

Verbal Judgment	Explanation	Fuzzy Number
Very Unimportant (1)	One criterion is significantly less important than another	(1, 1, 2)
Less Important (2)	One criterion is slightly less important than another	(1, 2, 3)
Equally Important (3)	Both criteria contribute equally to the objective	(2, 3, 4)
More Important (4)	One criterion is somewhat preferred over another	(3, 4, 5)
Very Important (5)	One criterion is strongly preferred over another	(4, 5, 5)

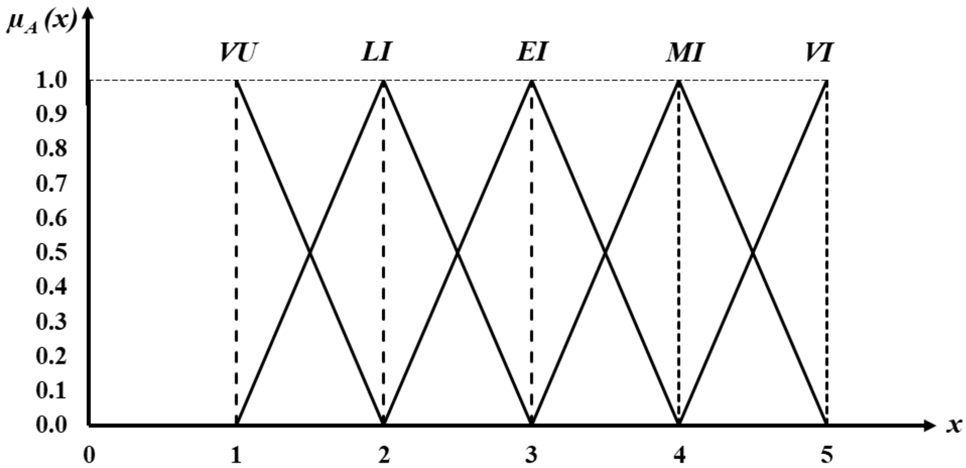

Figure 2. The membership functions of the fuzzy numbers for linguistic values.

The fuzzy comparison matrix, Ã, representing fuzzy relative importance of each pair of elements, is given by Equation (1), written as follows:

$$\tilde{A} = \begin{bmatrix} 1 & \tilde{a}_{12} & \tilde{a}_{13} & \cdots & \tilde{a}_{1n} \\ \tilde{a}_{21} & 1 & \tilde{a}_{23} & \cdots & \tilde{a}_{2n} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ \tilde{a}_{n1} & \tilde{a}_{n2} & \cdots & \cdots & 1 \end{bmatrix} \textit{where, } \tilde{a}_{ii} = 1,\ \tilde{a}_{ij} = \tilde{a}_{ji},\ \tilde{a}_{ij} \neq 0 \quad (1)$$

The suggested approach uses representative membership values to characterize each reciprocal fuzzy number instead of the inverse and reverse order of its corresponding positive fuzzy number. For example, if $\tilde{a}_{ij}$ is assessed as "more important", a positive judgment represented by (3, 4, 5), its reciprocal element $\tilde{a}_{ji}$ results in "less important", a negative judgment characterized by (1, 2, 3). This approach assists the operations of pairwise comparison and provides a more accurate representation of human assessments. The concept of ∝-cut is applied to account for specific levels of uncertainty in the decision-making process. The value ∝ is between 0 and 1. Where, $\propto = 0$ and $\propto = 1$, signify the degree of uncertainty as greatest and least, respectively. Selecting $\propto = 0.5$ indicates that environmental uncertainty is steady. Figure 3 shows that a triangular fuzzy number regarding a given value can be denoted by $(X_{\propto,L}, X_{\propto,M}, X_{\propto,U})$. $X_{\propto,M}$, $X_{\propto,L}$, and $X_{\propto,U}$ represents the most likely, minimum, and maximum values of the fuzzy number, respectively. The five membership functions can be mathematically represented by Equations (2)–(6), written as follows:

$$X(\propto)_{\text{Very unimportant}} = \begin{cases} 1 \\ 1 \\ 2-\propto \end{cases} \tag{2}$$

$$X(\propto)_{\text{Less important}} = \begin{cases} 1+\propto \\ 2 \\ 3-\propto \end{cases} \tag{3}$$

$$X(\propto)_{\text{Equally important}} = \begin{cases} 2+\propto \\ 3 \\ 4-\propto \end{cases} \tag{4}$$

$$X(\propto)_{\text{More important}} = \begin{cases} 3+\propto \\ 4 \\ 5-\propto \end{cases} \tag{5}$$

$$X(\propto)_{\text{Very important}} = \begin{cases} 4+\propto \\ 5 \\ 5 \end{cases} \tag{6}$$

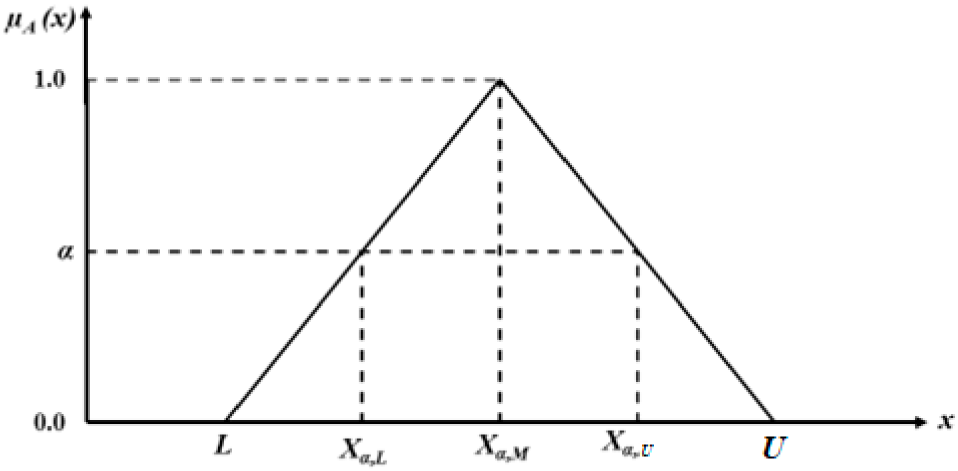

Figure 3. Triangular fuzzy intervals under ∝-cuts.

Accordingly, a fuzzy comparison matrix can be defined as follows:

$$\tilde{A} = \begin{bmatrix} 1 & (X_{12,L}, X_{12,M}, X_{12,U}) & \cdots & (X_{1n,L}, X_{1n,M}, X_{1n,U}) \\ (X_{21,L}, X_{21,M}, X_{21,U}) & 1 & \cdots & (X_{2n,L}, X_{2n,M}, X_{2n,U}) \\ \cdots & \cdots & \cdots & \cdots \\ (X_{n1,L}, X_{n1,M}, X_{n1,U}) & (X_{n2,L}, X_{n2,M}, X_{n2,U}) & \cdots & 1 \end{bmatrix} \tag{7}$$

For instance, $(x_{12,L}, x_{12,M}, x_{12,U})$ in Equation (7) displays the first element's lower, middle, and upper values in relation to the second element at the higher level, respectively. To facilitate fuzzy weight calculations, matrix $\tilde{A}$ is further divided into three crisp matrices: the lower bound matrix (A_L), most likely matrix, (A_M), and upper-bound matrix (A_U). These non-fuzzy comparison matrices are given by the following:

$$A_L = \begin{bmatrix} 1 & X_{12,L} & \cdots & X_{1n,L} \\ X_{21,L} & 1 & \cdots & X_{2n,L} \\ \cdots & \cdots & \cdots & \cdots \\ X_{n1,L} & \cdots & \cdots & 1 \end{bmatrix} A_M = \begin{bmatrix} 1 & X_{12,M} & \cdots & X_{1n,M} \\ X_{21,M} & 1 & \cdots & X_{2n,M} \\ \cdots & \cdots & \cdots & \cdots \\ X_{n1,M} & \cdots & \cdots & 1 \end{bmatrix} A_U = \begin{bmatrix} 1 & X_{12,U} & \cdots & X_{1n,U} \\ X_{21,U} & 1 & \cdots & X_{2n,U} \\ \cdots & \cdots & \cdots & \cdots \\ X_{n1,U} & \cdots & \cdots & 1 \end{bmatrix} \tag{8}$$

2.3. Relative Weight Calculations

When calculating local weights, the normalization of the geometric mean (NGM) approach applied in Buckley's model is utilized and yielded by Buckley [29] Equations (9) and (10), written as follows:

$$w_i = \frac{g_i}{\sum_{i=1}^{n} g_i} \tag{9}$$

$$g_i = \left(\prod_{j=1}^{n} a_{ij}\right)^{1/n} \tag{10}$$

In Equations (9) and (10), g_i is geometric mean of criterion i, a_{ij} is the comparison value of criterion i to criterion j, w_i is the i-th criterion's weight, where $w_i > 0$ and $\sum_{i=1}^{n} w_i = 1$, $1 \leq i \leq n$. The maximum eigenvalue λ_{max} is calculated as follows (Equation (11)):

$$\lambda_{max} = Q\, w^T \tag{11}$$

where Q is the sum of each column of matrix, Q is a vector size equal $(n \times 1)$, and w^T is the normalized vector $(1 \times n)$. Accordingly, the overall weight of the l-th sub-criterion, S_l, can be computed by Equation (12), written as follows:

$$s_l = w_K \times s_{lk} \tag{12}$$

where w_k is the weight of the k-th main criterion; S_{lk} is the local weight of the l-th sub-criterion with respect to the k-th main criterion. By the same manner, the weight of m-th alternative with respect to the l-th sub-criterion (e_{lm}) can be obtained. The overall weight of the m-th alternative regarding the l-th sub-criteria, (r_m) is given by Equation (13), written as follows:

$$r_m = s_l \times e_{ml} \tag{13}$$

Finally, the overall weight of the m-th alternative regarding all sub-criteria, R_m, can be found by Equation (14), written as follows:

$$R_m = \sum_{k=1}^{k} s_l \times e_{ml} \tag{14}$$

2.4. Consistency Checks

If the maximum eigenvalue λ_max = n, where n is the matrix size, then the comparison matrix is consistent. The deviation of the judgments is measured using the consistency index (CI), which is defined and stated by Saaty [30] Equation (15), written as follows:

$$CI = \frac{\lambda max - n}{n - 1} \tag{15}$$

Given the same values from randomly generated matrices, the consistency ratio (CR) is determined using Equation (16), written as follows:

$$CR = \frac{CI}{RI} \tag{16}$$

The random index (RI) simulates numerous pairwise comparisons that are created at random for varying matrix sizes Saaty [30]. To be considered acceptable, the value of CR must be 10% or less. In some circumstances, a limit of 20% may be accepted [14]. It should be emphasized, nevertheless, that we may find values considerably bigger than 0.10 due to the fuzzy structure of the model and the left (pessimistic) leaning of some decisions and the right (optimistic) leaning of others. That's still okay if you can figure out what's causing the difference. As λ_{max} represents a triangular number computed individually for matrices A_L, A_M and A_U using Equation (8) for each decision-maker, the recommendation by Durán and Aguilo [31] is to employ the central value of λ_max. This suggestion stems from the symmetry inherent in triangular numbers, where the central value aligns with the centroid of the triangular area. Consequently, it is advocated to calculate λ_{max}, along with CI and CR, specifically for the matrix A_M.

2.5. Synthesis of Group Decisions

After determining the relative weight, it is necessary to combine the opinions of several evaluators into one. The average weight is used in this work because it is a simple and faster method than most similar ones. When a fuzzy number needs to be converted to a single representative value, defuzzification is crucial. The three fuzzy numbers' lower, middle, and upper values are defuzzified into a single crisp value (Equations (17) and (18)).

$$w_l = \frac{\sum_{n=1}^{n} w_{l,n}}{n}, \; w_m = \frac{\sum_{n=1}^{n} w_{m,n}}{n}, \; w_u = \frac{\sum_{n=1}^{n} w_{u,n}}{n} \tag{17}$$

$$\mathrm{M}_{crisp} = \frac{w_l + 4w_m + w_u}{6} \tag{18}$$

where w_l, w_m, and w_u represent the lower, middle, and upper final weights assigned to the main criteria, sub-criteria, and alternatives, respectively. Additionally, n denotes the number of experts involved in the evaluation process.

All fuzzy AHP calculations, including the construction of pairwise comparison matrices, consistency checks, and synthesis of group decisions, were performed using Microsoft Excel. Custom Excel templates were developed to implement the fuzzy AHP steps, including the use of triangular fuzzy numbers and defuzzification formulas. This approach ensured transparency, reproducibility, and ease of validation for the calculations presented in this study.

3. Case Study and Model Implementation

A real-world problem is addressed by the use of the proposed framework; the process followed is illustrated in Figure 4. These steps were performed after defining the overall goal, which is selecting the appropriate ESS.

3.1. Criteria Hierarchy Development

The decision problem was broken down to create a hierarchy of criteria. As seen in Figure 5, nodes in the hierarchy stand in for primary criteria with sub-criteria. Figure 5 illustrates the hierarchical structure of the decision-making framework, with the selection of the optimal excavation support system as the overarching goal at Level 1. Level 2 comprises the two primary criteria: safety (encompassing structural stability) and cost (covering economic feasibility). These criteria branch into Level 3 sub-criteria: Safety includes soil condition, underground water condition, excavation depth, and adjacent buildings, while cost consists of construction cost, progress rate, and crossing utilities. This structure, validated through expert input and aligned with industry standards, systematically organizes the critical factors influencing ESS selection.

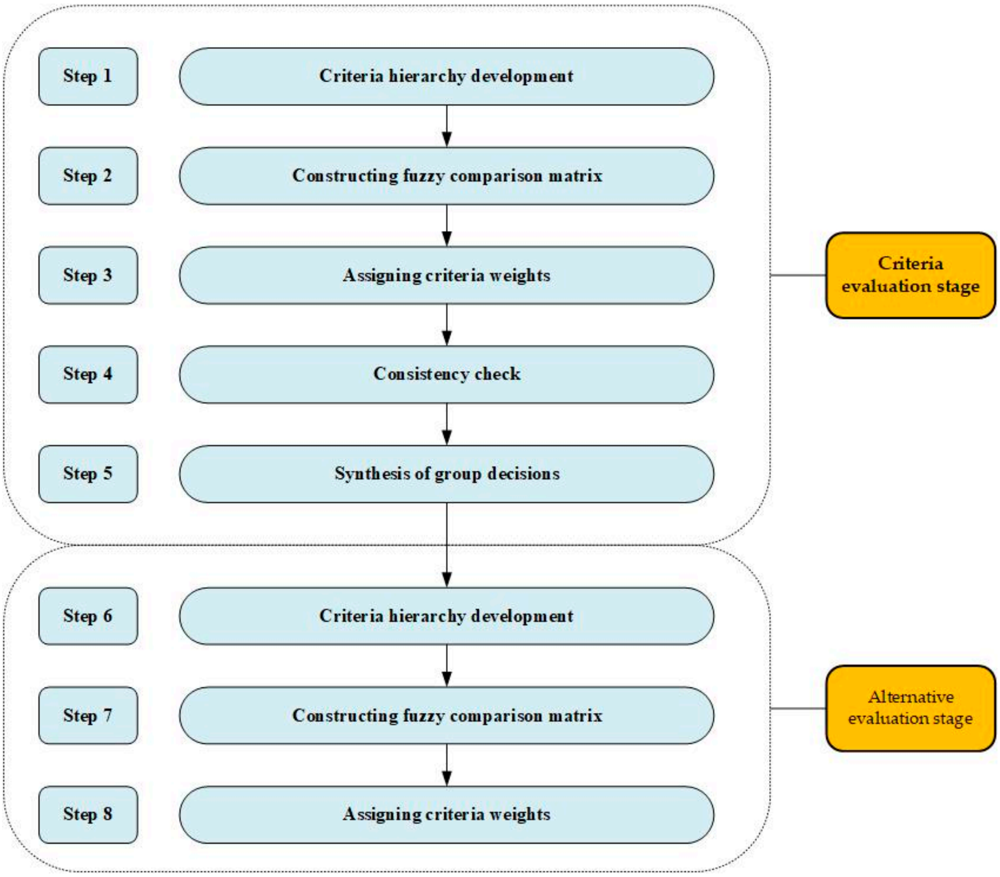

Figure 4. Schematic diagram of the proposed model implementation.

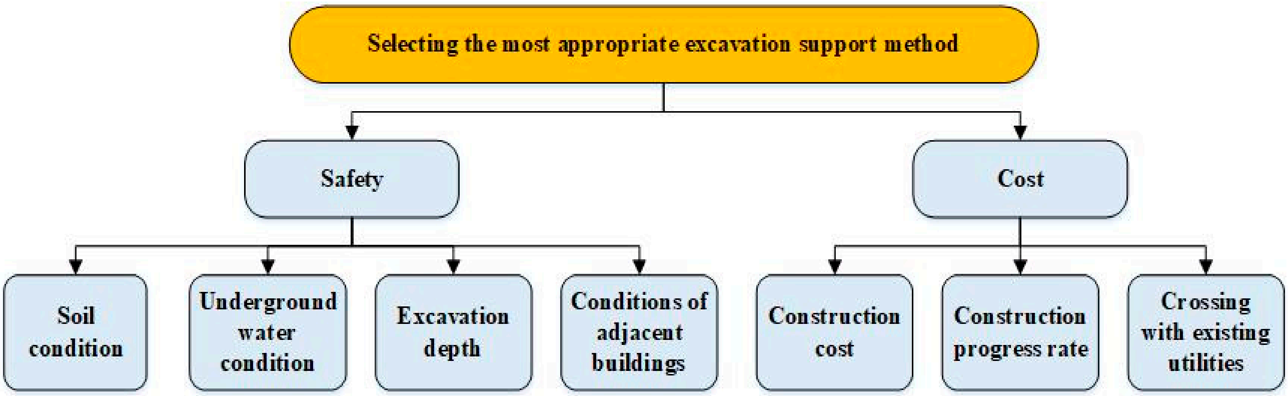

Figure 5. Schematic diagram of the proposed model's criteria hierarchy.

3.2. Constructing Fuzzy Comparison Matrix

Ten experts made up the decision committee that evaluated the pairwise comparisons after the hierarchy was established. Those experts were instructed to offer their comparison judgments using the linguistic scale specified in Figure 1 through a series of questionnaires constructed based on Figure 4. For every criterion in the hierarchy, comparisons were carried out independently. Questionnaires were created specifically for each of the three tiers of the hierarchy. Table 3 displays the questionnaire that was used to assess the sub-criteria. Tables 4 and 5 present the comparative findings of all primary criteria with respect to the overall goal and sub-criteria with respect to the main criteria, respectively.

Table 3. Questionnaire used to evaluate sub-criteria Pan [28].

Question No.	Comparison Criteria	Question
Q1	Soil Condition vs. Underground Water Condition	How does the significance of soil condition compare to that of underground water condition?
Q2	Soil Condition vs. Excavation Depth	How does the significance of soil condition compare to excavation depth?
Q3	Soil Condition vs. Condition of Adjacent Buildings	How does the significance of soil condition compare to the condition of adjacent buildings?
Q4	Underground Water Condition vs. Excavation Depth	How does the significance of underground water condition compare to excavation depth?
Q5	Underground Water Condition vs. Condition of Adjacent Buildings	How significant is underground water condition compared to the condition of adjacent buildings?
Q6	Excavation Depth vs. Condition of Adjacent Buildings	How significant is excavation depth compared to the condition of adjacent buildings?

Table 4. Assessment of results of the main criteria regarding the overall goal.

Pairwise Criteria	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th
Safety vs. cost	4	4	3	3	3	4	5	4	4	3

Table 5. Assessment results of the sub-criteria with respect to safety.

Pairwise Criteria	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th
Soil vs. water	3	3	5	3	3	2	2	3	3	3
Soil vs. depth	3	5	5	3	3	4	3	3	3	4
Soil vs. adjacent	4	5	5	3	3	4	3	3	5	3
Water vs. depth	3	5	5	3	3	4	3	3	3	5
Water vs. adjacent	3	4	5	3	3	3	4	3	4	3
Depth vs. adjacent	3	4	5	3	3	4	3	3	3	4

3.3. Assigning Criteria Weights

Only the pairwise comparison assessments of the first and second experts' findings regarding safety (B1) in relation to soil condition (B11), underground water condition (B12), excavation depth (B13), and condition of nearby buildings (B14) are provided to improve the comprehensibility of the proposed model's methodology. First, applying the fuzzy numbers defined in Figure 1 and Equations (2)–(6), the fuzzy comparison matrices of ^{1} under $\propto = 0.5$ are given by the following:

$$\tilde{A}^1 \quad \begin{array}{ccccc} & B11 & B12 & B13 & B14 \\ B11 & 1 & (2.5, 3, 4.5) & (2.5, 3, 4.5) & (3.5, 4, 4.5) \\ B12 & (2.5, 3, 4.5) & 1 & (2.5, 3, 4.5) & (2.5, 3, 4.5) \\ B13 & (2.5, 3, 4.5) & (2.5, 3, 4.5) & 1 & (2.5, 3, 4.5) \\ B14 & (1.5, 2, 3.5) & (2.5, 3, 4.5) & (2.5, 3, 4.5) & 1 \end{array}$$

The first row in ^{1} represents the relative preference given by the first expert from Table 5. Applying Equations (8)–(10) the lower bound matrix $\tilde{A}_L^1$ and eigenvector estimation are derived as shown in Table 6.

Table 6. Lower bound matrix and eigenvector calculations.

Safety		B11	B12	B13	B14		
$\tilde{A}_L^1$	B11	1	2.5	2.5	3.5	$(1 \times 2.5 \times 2.5 \times 3.5)^{1/4} = 2.16$	$(2.16/7.89) = 0.27$
	B12	2.5	1	2.5	2.5	$(2.5 \times 1 \times 2.5 \times 2.5)^{1/4} = 1.99$	$(1.99/7.89) = 0.25$
	B13	2.5	2.5	1	2.5	$(2.5 \times 2.5 \times 1 \times 2.5)^{1/4} = 1.99$	$(1.99/7.89) = 0.25$
	B14	1.5	2.5	2.5	1	$(1.5 \times 2.5 \times 2.5 \times 1)^{1/4} = 1.75$	$(1.75/7.89) = 0.23$
$\sum$		7.5	8.5	8.5	9.5	7.89	1.00

The matrices $\tilde{A}_M^1$ and $\tilde{A}_U^1$, corresponding to the first and second experts, respectively, can also be determined. The eigenvector of $\tilde{A}_L^1$ is found to be (0.27, 0.25, 0.25, 0.23) (0.27, 0.25, 0.25, 0.23) (0.27, 0.25, 0.25, 0.23), where each value, ordered from left to right, represents the weight of the weight of B11 corresponding to B12, B13, and B14, respectively. Following the same approach, the eigenvectors for for $\tilde{A}_M^1$ and $\tilde{A}_U^1$ are obtained as (0.27, 0.25, 0.25, 0.23) and (0.27, 0.25, 0.25, 0.23), respectively. Consequently, the eigenvector for B11 is given by (0.27, 0.27, 0.27) (0.27, 0.27, 0.27) (0.27, 0.27, 0.27), representing its lower, middle, and upper relative weights.

Similarly, the computed relative weights for B12, B13, and B14 are (0.25, 0.25, 0.25) (0.25, 0.25, 0.25) (0.25, 0.25, 0.25), (0.25, 0.25, 0.25) (0.25, 0.25, 0.25) (0.25, 0.25, 0.25), and (0.22, 0.23, 0.23) (0.22, 0.23, 0.23) (0.22, 0.23, 0.23), respectively. Applying the same methodology to the second expert's pairwise comparisons, the relative weights for B11 corresponding to B12, B13, and B14 are determined as (0.34, 0.34, 0.32), (0.32, 0.33, 0.31), (0.18, 0.17, 0.19), and (0.16, 0.17, 0.18) respectively.

3.4. Consistency Checks

Consistency checks are performed subsequent to the estimation of relative weights. It is possible to determine the eigenvalue λ_{max} for the medium matrix $\tilde{A}_M^1$ with respect to the first expert by using Equation (11) as follows:

$$\lambda_{max} = 9 \times 0.27 + 10 \times 0.25 + 10 \times 0.25 + 11 \times 0.23 = 9.96$$

Equations (15) and (16) are used to obtain CR and CI, in that order, according to Saaty [30], where RI is 0.56 and 0.9, respectively, meaning that $n = 3$ and 4.

$$\mathrm{CI} = \frac{9.96 - 4}{4 - 1} = 1.98$$

$$\mathrm{CR} = \frac{1.98}{0.9} = 2.20$$

The fact that every CI and CR value is greater than zero suggests that the comparative evaluations based on the opinions of ten experts are reliable [32].

3.5. Synthesis of Group Decisions

These two distinct experts' measurements are grouped. Concerning soil condition by using Equation (17) as follows:

$$w_L = \frac{0.27 + 0.34}{2} = 0.31,\ w_M = \frac{0.27 + 0.34}{2} = 0.31,\ \text{and}\ w_U = \frac{0.27 + 0.32}{2} = 0.30$$

Consequently, Equation (18) can be used to estimate the weight of soil condition as follows:

$$M_{\text{soil condition}} = \frac{0.31 + 4 \times 0.31 + 0.30}{6} = 0.30$$

Therefore, by applying the same procedures, the final weights of the main criteria regarding the overall goal and under $\propto = 0.5$ are safety (0.56) and cost (0.44).

Likewise, the final sub-criteria weights regarding the main criteria under $\propto = 0.5$ result in Table 7.

Table 7. Sub-criteria weights regarding the main criteria.

α	Soil Condition	Water Condition	Excavated Depth	Adjacent Buildings	Construction Cost	Progress Rate	Crossing Utilities
0.5	0.281	0.277	0229	0.212	0.416	0.294	0.295

Using Table 7's weights for the primary criteria and Equation (12), the results are displayed in Table 8. This yields the synthetic weights for the sub-criteria. For instance, the soil condition's synthetic weight at $\propto = 0$ is calculated as follows:

$$r_{\text{soil condition}} = 0.281 \times 0.56 = 0.157$$

Table 8. Synthetic sub-criteria weights regarding the main criteria.

α	Soil Condition	Water Condition	Excavated Depth	Adjacent Buildings	Construction Cost	Progress Rate	Crossing Utilities
0.5	0.157	0.155	0.128	0.118	0.183	0.129	0.129

3.6. Alternatives Evaluation

This paper presents a case study of the Pfizer solid oral dosage production facility at El Nozha, Cairo, Egypt. The two-story, 3000 m^2 facility, constructed between 2012 and 2013, includes an underground water tank requiring a 30,000 m^3 excavation (3000 m^2 area $\times$ 10 m depth) in predominantly sandy soil. During planning, the contractor evaluated four ESS: diaphragm walls, secant piles, sheet piles, and soldier piles. The 10-m excavation depth and low-cohesion soil necessitated a rigorous ESS selection process, prioritizing waterproofing and structural stability. Diaphragm walls were ultimately chosen for their superior performance in sandy conditions.

The evaluation of these alternatives was conducted by a project decision-making group consisting of three experienced professionals: the project manager, the construction manager, and the consultant engineer. They have over ten years of experience in planning, designing, and constructing excavation works in Egypt, ensuring that the assessment reflected both technical rigor and local industry knowledge, as illustrated in Table 9. The total planned duration for the project was 18 months, with the excavation depth for the underground tank specified at 10 m. The rigorous assessment process, leveraging the collective experience of the decision team, ensured a comprehensive and context-sensitive evaluation of the available ESSs tailored to the unique requirements of this facility.

Table 9. Expert panel: roles, education, and experience.

Expert No.	Role	Education	Years of Experience	Area of Expertise
1	Project Manager	MSc Civil Engineering	15	Project management, excavation planning
2	Construction Manager	BSc Civil Engineering	13	Construction supervision, site operations
3	Consultant	PhD Geotechnical Engineering	20	Geotechnical design, excavation support systems

To determine the most suitable excavation method for the project's specific requirements, discussions focused on four alternatives: diaphragm wall, secant pile, soldier pile, and sheet pile. Leveraging their expertise, the evaluators engaged in a rigorous process of fuzzy comparisons to derive judgments and evaluations. Additionally, a comparative analysis was conducted for the four excavation construction systems concerning each sub-criterion. Notably, Table 9 presents the comparison outcomes with respect to soil condition. The values of λ_{max}, CI, and CR can also be referenced in Table 10, providing a comprehensive overview of the assessment results.

Table 10. Comparison results for alternative weights regarding the soil condition.

Alternative Comparisons	Results		
	1st Expert	2nd Expert	3rd Expert
Diaphragm wall vs. secant pile	2	2	3
Diaphragm wall vs. soldier pile	3	3	3
Diaphragm wall vs. sheet pile	4	3	3
Secant pile vs. soldier pile	5	5	4
Secant pile vs. sheet pile	5	5	4
Soldier pile vs. sheet Pile	3	3	3
λ_{max}	8.89	9.21	9.87
CI	1.63	1.73	1.95
CR	1.81	1.92	2.17

3.7. Determine the Final Ranking

The synthetic relative alternative weights relating to each sub-criterion shown in Table 11.

Table 11. Alternative weights regarding the sub-criteria.

Sub-Criteria	Alternatives				
	$\propto$	Diaphragm Wall	Secant Pile	Solider Pile	Sheet Pile
Soil condition	0.5	0.25	0.33	0.21	0.20
Underground water condition	0.5	0.24	0.30	0.25	0.22
Excavated depth	0.5	0.25	0.30	0.24	0.21
Adjacent buildings	0.5	0.25	0.25	0.25	0.25
Construction cost	0.5	0.31	0.27	0.22	0.20
Construction progress rate	0.5	0.27	0.32	0.26	0.15
Crossing utilities	0.5	0.22	0.28	0.19	0.32

3.8. Selecting the Appropriate System

Using Equation (13), it is possible to estimate the final alternative weight as indicated in Table 11. For instance, the weight of the secant pile considering the soil condition at $\propto = 0.5$ can be obtained by the following:

$$r_{\text{secant pile}} = 0.155 \times 0.33 = 0.051$$

Using Equation (14), the sum of all weights can be determined as shown in the last row of Table 12.

Table 11 demonstrates that the secant pile is the heaviest. The secant pile arrangement is therefore thought to be the best option. This result is consistent with the real system chosen for the Pfizer project. A higher weighting indicates the most suited option rather than necessarily a superior one.

Table 12. Overall alternatives weights assed by the proposed model.

Sub-Criteria	Alternatives				
	∝	**Diaphragm Wall**	**Secant Pile**	**Solider Pile**	**Sheet Pile**
Soil condition	0.5	0.039	0.052	0.033	0.031
Underground water condition	0.5	0.037	0.047	0.039	0.034
Excavated depth	0.5	0.032	0.038	0.031	0.027
Adjacent buildings	0.5	0.030	0.030	0.030	0.030
Construction cost	0.5	0.057	0.049	0.040	0.037
Construction progress rate	0.5	0.035	0.041	0.034	0.019
Crossing utilities	0.5	0.028	0.036	0.025	0.041
$\sum$	0.5	0.258	0.293	0.230	0.219

4. Discussion

The findings of this study underscore the efficacy of the proposed fuzzy AHP methodology in identifying the most appropriate ESS for construction projects. By integrating the subjective insights of industry experts and addressing the uncertainties inherent in decision-making, the fuzzy AHP model offers a reliable and structured framework for evaluating alternatives against multiple criteria. This section delves into the key insights, practical implications, and limitations of the study, providing a comprehensive understanding of its contributions and areas for future exploration.

The hierarchical structure developed for this study, as illustrated in Figure 5, successfully encapsulated the primary and sub-criteria critical to the selection of ESSs. The weighting of these criteria revealed their relative significance in the decision-making process. For example, safety emerged as the top priority with a weight of 0.56, surpassing cost at 0.44. This prioritization aligns with the construction industry's emphasis on ensuring structural stability and minimizing risks during excavation activities. Among the sub-criteria, soil condition (0.281) and underground water condition (0.277) were assigned the highest weights, reflecting their substantial influence on the stability and feasibility of ESSs. These results are consistent with real-world observations, as soil and groundwater conditions are often decisive factors in excavation planning.

The consistency of expert judgments was rigorously evaluated through consistency checks, including the calculation of CI and CR values. While some CR values exceeded the traditional threshold of 0.1, they were considered acceptable given the complexity of the decision problem and the involvement of multiple experts. This finding highlights the value of incorporating diverse perspectives for a well-rounded and reliable evaluation.

In evaluating alternative ESSs—diaphragm wall, secant pile, soldier pile, and sheet pile—the secant pile system emerged as the most suitable option, with a weight of 0.293. This outcome aligns with the system chosen for the Pfizer project, thereby validating the practical applicability of the proposed model. The secant pile system performed exceptionally well across several sub-criteria, particularly in soil condition (0.052), underground water condition (0.047), and construction progress rate (0.041). This indicates that the secant pile system balances safety, efficiency, and cost-effectiveness, making it a robust choice for similar projects.

5. Practical Implications

5.1. Relevance to Construction Practice

The fuzzy AHP approach introduced in this study has significant implications for the construction industry. By providing a structured and systematic method for evaluating ESSs, the model reduces reliance on subjective intuition and enhances the transparency and reliability of decision-making. It emphasizes the importance of considering multiple criteria, such as soil conditions, groundwater levels, and proximity to adjacent structures, which are often overlooked or underestimated in traditional decision-making processes. This study is a valuable resource for raising awareness among industry professionals about the need for a holistic and data-driven approach to selecting ESSs. Moreover, its ability to incorporate uncertainties and expert judgments ensures its relevance across various applications.

5.2. Benefits of the Fuzzy AHP Approach

Adopting the fuzzy AHP approach in this study provides significant advantages over traditional decision-making methods for selecting ESSs in construction projects. First, it addresses the inherent uncertainty and subjectivity often encountered when experts express their judgments in linguistic rather than numerical terms. By incorporating fuzzy logic, the model captures the imprecise nature of human assessments more realistically, leading to a more robust and reliable prioritization of criteria and alternatives. Second, the method enhances transparency and consistency by structuring complex multi-criteria evaluations into a clear and systematic framework. This improves the quality of decisions and increases stakeholder confidence in the outcomes. Third, the fuzzy AHP model demonstrates flexibility and adaptability, making it applicable to various construction scenarios where site conditions, environmental risks, and technical requirements vary significantly. The model's ability to synthesize diverse expert opinions and defuzzify the results into crisp, actionable priorities further ensures that decision-makers can make informed choices even in complex and uncertain environments. Finally, the successful application of the fuzzy AHP method in the Pfizer project case study, where the selected system aligned with real-world decisions, validates its practical utility and highlights its potential for broader use in enhancing construction projects.

5.3. Potential Broader Applications

Beyond ESS selection, the fuzzy AHP approach demonstrated in this study holds significant potential for broader applications across various construction and civil engineering areas. Its ability to integrate expert judgment with uncertainty modeling makes it an ideal tool for complex decision-making scenarios where multiple, often conflicting, criteria are considered. For instance, it can be applied to optimize the selection of foundation systems, construction materials, contractor selection, and project delivery methods. Moreover, in large-scale infrastructure projects such as tunnels, bridges, and metro systems, where ground conditions and stakeholder requirements are highly variable, the fuzzy AHP framework can guide engineers and managers toward more balanced and sustainable solutions. By extending its use beyond the excavation context, the fuzzy AHP method can support a wide range of decision-making needs in the construction industry, ultimately promoting more informed, transparent, and resilient project outcomes.

6. Limitations and Future Research

6.1. Study Limitations

While effective, the proposed fuzzy AHP model has some limitations that should be acknowledged. First, the model relies on expert judgments, which may introduce bias due to subjective experiences or preferences despite fuzzy logic mitigating such subjectivity. Second, its validation is based on a single case study, limiting generalizability to other regions or construction contexts. Third, the framework is static and does not account for dynamic site conditions, such as unexpected groundwater changes or adjacent structure movements, which could impact system performance. Finally, the model assigns equal weight to all expert opinions, overlooking potential variations in expertise, which could skew results.

Additionally, although the current criteria hierarchy was developed based on literature review and expert consultation, factors such as contractor experience and equipment availability were not included. The exclusion of these factors may limit the comprehensiveness of the model.

6.2. Opportunities for Future Research

Future research should focus on enhancing the model's robustness and applicability. One direction is validating the framework through multiple case studies across diverse conditions to ensure broader reliability. Another opportunity includes the use of machine learning that could refine expert judgments by analyzing historical data, reducing bias, and optimizing decision-making. Additionally, hybrid approaches combining fuzzy AHP with other MCDM methods (e.g., TOPSIS) could better capture complex uncertainties. Moreover, future research will aim to incorporate other context-specific criteria to further improve decision-making accuracy and model robustness.

6.3. Recommendations for Practice

To facilitate practical adoption, construction firms should pilot the fuzzy AHP model on small-scale projects to evaluate its feasibility before full implementation. Training programs for engineers and project managers are essential to ensure accurate pairwise comparisons and consistency checks. Developing user-friendly software and automating calculations, streamlining integration into project management workflows. Collaborative platforms for knowledge sharing among industry experts would help refine criteria hierarchies and linguistic scales based on collective insights. Additionally, maintaining dynamic libraries of excavation support criteria updated with new materials, technologies, and regulations would ensure the model remains aligned with industry advancements, ultimately improving safety and cost in excavation projects.

7. Conclusions

This study's proposed fuzzy AHP model provides a practical and reliable framework for selecting excavation support systems in construction projects. The model effectively addresses the complexities and uncertainties inherent in decision-making by balancing critical factors such as safety and cost-effectiveness. The case study of the Pfizer project demonstrates the model's effectiveness, with the secant pile system emerging as the most suitable option. This outcome aligns with the actual system chosen for the project, validating the model's practical applicability and its ability to replicate real-world decisions.

The study's findings reveal several key insights. First, the hierarchical structure of the decision problem successfully captured the primary criteria (safety and cost) and sub-criteria (soil condition, underground water condition, excavation depth, and adjacent buildings) that influence the selection process. Safety was prioritized with a weight of 0.56, reflecting the construction industry's emphasis on minimizing risks and ensuring structural stability. Among the sub-criteria, soil condition (0.281) and underground water condition (0.277) were identified as the most critical factors, underscoring their significant impact on excavation stability and feasibility.

Second, the consistency checks performed on the pairwise comparison matrices confirmed the reliability of the expert judgments, despite some CR values exceeding the conventional threshold. This highlights the importance of incorporating diverse perspectives to achieve a comprehensive and balanced evaluation. The evaluation of alternative excavation support systems—diaphragm wall, secant pile, soldier pile, and sheet pile—revealed that the secant pile system (0.293) was the most suitable option for the Pfizer project. The secant pile system performed exceptionally well across multiple sub-criteria, particularly in soil condition (0.052), underground water condition (0.047), and construction progress rate (0.041), demonstrating its balanced combination of safety and cost-effectiveness.

In summary, this study highlights the value of integrating fuzzy AHP into construction decision-making processes, providing a structured and systematic approach to address complex, multi-criteria problems. It serves as a foundation for further research and innovation, paving the way for more robust and adaptive decision-making tools in the construction industry. By advancing safer, more efficient, and cost-effective construction practices, the proposed model contributes to the ongoing evolution of construction management and engineering.

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