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STRATEGIC DECISION-MAKING IN UNCERTAINTY: INTEGRATING FORWARD-LOOKING SCENARIO PLANNING AND MULTI-CRITERIA ANALYSIS FOR ADAPTIVE REUSE PROJECTS

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ABSTRACT

Background and aim. Adaptive reuse enhances circularity by repurposing buildings, reducing carbon emissions, and preserving heritage. However, decision-making is complex due to stakeholder conflicts, regulations, and uncertainties. This study introduces an integrated framework combining Cross-Impact Balance (CIB) analysis, the Analytic Hierarchy Process (AHP), and Fuzzy-TOPSIS to support structured, participatory decision-making.

Methods and Data. A mixed-method approach integrates CIB for scenario development, AHP for stakeholder-driven prioritization, and Fuzzy-TOPSIS for ranking reuse scenarios. A hypothetical case study demonstrates the framework's applicability.

Findings. The integration of CIB, AHP, and Fuzzy-TOPSIS provides a structured decision-making approach that enhances scenario coherence, aligns decisions with stakeholder priorities, and improves scenario ranking robustness. The framework enables systematic exploration of adaptive reuse scenarios, ensuring alignment with stakeholder objectives.

Theoretical / Practical / Societal implications. Theoretically, this study advances scenario-based decision-making by integrating scenario development and decision-making approaches, addressing gaps in adaptive reuse decision frameworks. Practically, it provides policymakers, urban planners, and developers with a structured tool to navigate complex decision-making in adaptive reuse projects. Societally, it supports sustainable and inclusive urban development by fostering consistent, long-term strategies that balance environmental, economic, and social considerations.

KEYWORDS: Adaptive Reuse, Circularity, Cross-Impact Balance (CIB) Analysis, Multi-criteria Decision-Making, Scenario Planning,

1 INTRODUCTION

The adaptive reuse of buildings has become a cornerstone strategy for promoting circularity in the built environment (Foster, 2020). By repurposing existing structures, adaptive reuse significantly reduces CO_2 emissions, curbs the extraction of virgin materials, and conserves valuable resources (Shahi et al., 2020). This approach directly supports global sustainability goals and addresses critical urban challenges, including resource scarcity and environmental degradation (Conejos, 2013). However, despite its promise, adaptive reuse decision-making processes remain complex and uncertain (Yung & Chan, 2012). These projects often involve a diverse set of stakeholders with conflicting interests and must navigate a range of regulatory, economic, and technical constraints (Wilkinson, 2014). Consequently, the strategies chosen for adaptive reuse are often limited to short-term perspectives and a narrow set of options, hindering their potential to achieve long-term sustainability and circularity (Greco et al., 2024; Vardopoulos et al., 2021). To address the intricacies and uncertainties of adaptive reuse decision-making, a range of tools and methodologies has been developed (Nedeljkovic et al., 2023). Among these, multi-criteria decision-making (MCDM) models have gained considerable traction for evaluating adaptive reuse projects (Nadkarni & Puthuvayi, 2020). These models provide a structured framework for assessing and comparing alternatives by incorporating multiple criteria (Love et al., 2023). However, existing decision-making approaches tend to adopt either overly generalized frameworks; focused solely on functional reuse, or overly specific ones, which prioritize granular design considerations (van Laar et al., 2024). Both approaches often overlook the broader, long-

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term objectives required to achieve true sustainability and circularity. Furthermore, most frameworks rely either on quantitative methods like cost-benefit analyses (Sanchez et al., 2019), and lifecycle assessments (Foster, 2020), or on generic qualitative approaches to evaluate the feasibility of proposed interventions (Wilkinson, 2014). While these methods offer valuable insights into resource efficiency and financial viability, they often fail to account for nuanced, context-specific factors or integrate forward-looking scenario planning essential for addressing the dynamic nature of urban development.

Scenarios are particularly valuable for adaptive reuse decision-making because they offer comprehensive, future-oriented perspectives. They enable decision-makers to explore how various reuse strategies might perform under different environmental, social, and economic conditions (Weimer-Jehle, 2023). This foresight helps ensure that decisions are robust, flexible, and aligned with long-term sustainability and community goals (Bottero et al., 2022). Normative scenarios, which outline pathways to achieve specific objectives (van Notten et al., 2003), are especially relevant for adaptive reuse. They help stakeholders collaboratively develop a broad range of desirable futures, ensuring that decisions reflect shared values and strategic priorities. Despite their potential, scenario-based methods are underutilized in adaptive reuse (van Laar et al., 2024), often resulting in decisions that fail to anticipate future challenges or opportunities.

There is a pressing need for decision-making frameworks that are both future-oriented and capable of addressing the inherent uncertainty and complexity of adaptive reuse projects. Such frameworks must enable the development of nuanced, context-specific scenarios that incorporate normative objectives, reflect stakeholder priorities, and facilitate the ranking of alternatives based on quantitative and qualitative criteria. To address these gaps, this study introduces an integrated decision-making framework that combines Cross-Impact Balance (CIB) analysis with the Analytic Hierarchy Process (AHP) and Fuzzy-TOPSIS methods.

This research highlights the strength of combining these methodologies into a cohesive, stepwise framework, demonstrating how they can guide adaptive reuse decision-making in a structured yet flexible manner. Using a hypothetical adaptive reuse project, the study showcases how this approach facilitates scenario development, interdependency analysis, and the evaluation of alternatives under uncertainty. The main finding illustrates how these tools can be integrated into a systematic process that supports stakeholders in collaboratively designing and prioritizing adaptive reuse scenarios. This framework offers a practical pathway for addressing the complexity of adaptive reuse while aligning decisions with long-term sustainability and social responsibility goals.

2 BACKGROUND LITERATURE

Scenario development and Multi-Criteria Decision Making (MCDM) analysis are two complementary methodologies extensively used in decision-making processes involving complex systems, such as adaptive reuse. Scenario development enables the exploration of possible futures by considering various uncertainties (Weimer-Jehle, 2023), while MCDM provides a structured framework for evaluating and ranking alternatives against multiple criteria (Saaty, 1990). The integration of these methodologies has gained significant attention, for its potential to improve decision-making outcomes by combining qualitative and quantitative insights (Stewart et al., 2013).

2.1 SCENARIO DEVELOPMENT

Scenario development is a structured approach for envisioning possible future states of a system under uncertainty. Scenarios, described as: coherent, consistent, and plausible descriptions of potential futures, are categorized as exploratory, predictive, or normative (van Notten et al., 2003). Exploratory scenarios examine possible futures based on varying assumptions, aiding in visualizing outcomes. Predictive scenarios forecast likely futures based on current trends, while normative scenarios prescribe pathways to achieve specific goals (van Notten et al., 2003). The normative approach is particularly valuable for adaptive reuse decision-making, where alignment with sustainability goals and community values is essential (Gassner & Steinmüller, 2018). Scenario development methods can be categorized into quantitative, qualitative, and mixed-method approaches, each suited to different needs. Quantitative methods rely on mathematical modeling for precision but often limit stakeholder involvement and are less effective over long-term projections, as they tend to extrapolate trends and may give a false sense of certainty (Amer et al., 2013). In contrast, qualitative methods, like Intuitive Logics (IL), excel in addressing complex issues through nuanced, context-specific insights. However, they can oversimplify systems by focusing on a limited number of uncertainties, potentially overlooking critical factors (Rowe et al., 2017).

Mixed-method approaches effectively combine the strengths of both, integrating data-driven analysis with stakeholder input to foster comprehensive discussions about future possibilities (Symstad et al., 2017). An example is Cross-Impact Balance (CIB) analysis, a semi-quantitative method that uses systems theory to model integrative and holistic scenarios (Weimer-Jehle, 2006). By employing formal logic to structure quantitative and qualitative inputs, CIB generates internally consistent narrative scenarios based on interactions among drivers of change, making it particularly suitable for complex socio-technical systems (Weimer-Jehle, 2023).

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2.2 MULTI-CRITERIA DECISION-MAKING

Multi-Criteria Decision-Making (MCDM) methods, such as AHP (Analytic Hierarchy Process), Fuzzy TOPSIS, PROMETHEE, and VIKOR, are widely used for evaluating and ranking alternatives across multiple conflicting criteria (Sahoo & Goswami, 2023). AHP excels in hierarchically structuring complex problems, prioritizing criteria through pairwise comparisons, and aggregating stakeholder preferences into a unified priority structure, fostering consensus while respecting diverse perspectives (Saaty, 1990). Fuzzy TOPSIS, which extends the classical TOPSIS method, effectively manages vagueness and subjectivity by using fuzzy set theory to rank alternatives based on their closeness to ideal and negative ideal solutions (Chen, 2000).

Combining AHP and Fuzzy TOPSIS enhances decision-making by integrating AHP's hierarchical structuring and consistency checks with Fuzzy TOPSIS's capacity for handling uncertainty (Efe, 2016). This hybrid approach is particularly valuable for complex, uncertain environments, as it provides a structured yet flexible evaluation framework (Mathew et al., 2020). Such integrations have been applied successfully in fields like supply chain management (Patil & Kant, 2014), and urban planning (Dang et al., 2019), demonstrating their versatility and effectiveness. While the combination of AHP and Fuzzy TOPSIS effectively ranks uncertain alternatives based on stakeholder preferences, it often relies on externally provided options, highlighting the need for an integrated approach that develops and ranks scenarios concurrently.

2.3 INTEGRATION OF SCENARIO DEVELOPMENT AND MULTI-CRITERIA DECISION ANALYSIS

The integration of scenario development and MCDM addresses the limitations of each methodology when applied independently. Scenario development often lacks a structured mechanism to prioritize options within each scenario, while MCDM can be overly deterministic without considering the broader context of future uncertainties (Sahoo & Goswami, 2023). By combining these methods, decision-makers can evaluate the robustness of alternatives across different scenarios, incorporate qualitative and quantitative dimensions of uncertainty, and enhance stakeholder engagement by providing a more holistic view of decision impacts (Sahoo & Goswami, 2023).

Numerous frameworks integrate scenario development with multi-criteria decision-making (MCDM), typically following one of two approaches. The scenario-driven MCDM approach develops scenarios first and applies MCDM to rank alternatives within each scenario (Bottero et al., 2022). In contrast, the MCDM-driven approach uses MCDM criteria to shape scenarios, aligning them with decision priorities (Della Spina, 2020). These frameworks have been applied in various fields, including urban planning, supply chain management, and engineering . However, these studies often face limitations, such as relying on a limited number of scenarios that fail to capture the full range of possibilities. Many frameworks lack consistency calculations, reducing the coherence and realism of the scenarios (Weimer-Jehle, 2006). Additionally, there is an overemphasis on predictive scenarios and mathematical models, prioritizing quantitative precision over qualitative insights and stakeholder perspectives (Weimer-Jehle, 2023). These shortcomings diminish the robustness and practical applicability of the scenarios in addressing complex challenges.

The Cross-Impact Balance (CIB) method overcomes these challenges by generating numerous consistent and plausible scenarios through a combination of qualitative and quantitative inputs (Weimer-Jehle, 2023). This makes it particularly effective for exploring complex systems. However, CIB has not been fully integrated with MCDM methods like AHP or Fuzzy TOPSIS, which excel at prioritizing and ranking alternatives. Combining these approaches offers significant potential, enabling the systematic creation, evaluation, and prioritization of scenarios within a unified framework. In a participatory setting, this integration enhances stakeholder engagement by involving them in the entire process, from scenario development to ranking, ensuring scenarios are aligned with diverse preferences and easing the adoption of the chosen scenario through consensus and trust in the outcomes.

3 STEPWISE APPROACH FOR COMBINING CROSS-IMPACT BALANCE ANALYSIS, AHP AND THE FUZZY TOPSIS METHODS

This section outlines a structured, multi-step framework tailored for decision-making in normative, uncertain, and complex contexts such as adaptive reuse projects (Figure 1). By integrating Cross-Impact Balance (CIB) analysis, the Analytic Hierarchy Process (AHP), and Fuzzy-TOPSIS methodologies, this approach effectively addresses the uncertainties inherent in adaptive reuse. It enables stakeholders to collaboratively assess, develop, and prioritize reuse scenarios, demonstrating its application through a hypothetical example of an adaptive reuse project.

3.1 STEP 1: DEFINE THE AIM AND OBJECTIVES

The first step establishes the foundation for the decision-making process by ensuring a clear understanding of the project's scope and goals. To create normative scenarios; future pathways that are achievable (van Notten et al., 2003), this step focuses on defining objectives that will guide subsequent scenario development. Stakeholders collaborate to articulate the overarching goal and themes, identify desired objectives, and determine the criteria

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necessary to evaluate progress toward these objectives. To balance adequacy and completeness in the scenario analysis, it is recommended to include 9–15 objectives for the development of descriptors and variants in Step 2, in line with the methodological guidelines of Weimer-Jehle, (2023). By addressing these critical elements, this step provides a structured and goal-oriented process fostering clarity, alignment, and a shared vision among all stakeholders.

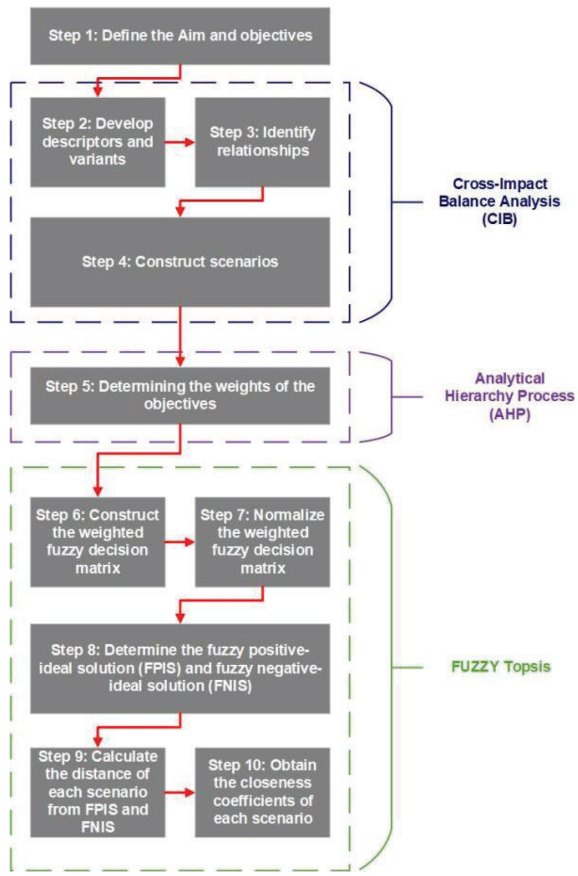

Figure 1: Stepwise approach for combining cross-impact balance analysis (CIB), AHP and the Fuzzy TOPSIS methods

3.2 STEP 2: DEVELOP DESCRIPTORS AND VARIANTS

The CIB method uses systems theory and formal logic to create internally consistent scenarios based on interacting drivers of change, integrating both qualitative and quantitative inputs (Weimer-Jehle, 2006). A key step in this process is identifying descriptors; 'critical factors defining the system' and their associated variants, which represent specific states these factors can assume (Weimer-Jehle, 2023). Descriptors should be developed at a high aggregation level (Weimer-Jehle, 2023), with each descriptor representing one objective, that can be supported by related criteria and / or a narrative that explains the descriptor's role and significance within the system. Variants then enable systematic exploration of scenarios by capturing the range of possible outcomes for each descriptor. For example, in adaptive reuse projects, "Environmental impact" could be a descriptor for the objective: 'Reducing environmental impact of the building', with variants such as "Low," "Medium," and "High." Stakeholders are encouraged to assign descriptive names and narratives to variants for clarity and effective communication, keeping 2–4 variants per descriptor as recommended by (Weimer-Jehle, 2023). The CIB analysis requirements of completeness (descriptor variants must cover all possible futures), mutual exclusivity (each development aligns with only one variant), and absence of overlap (variants of different descriptors must address distinct topics) should also be taken into account when developing variants (Weimer-Jehle, 2023).

Although the CIB methodology supports variants with various characteristics (ordinal, nominal, or ratio) this paper focuses on descriptors with ordinal measurement scales. For instance, "user demand" as a descriptor might include ordinal variants like "Low," "Medium," and "High," reflecting their ranked importance. This approach simplifies the system, making it possible to translate qualitative ordinal variants into linguistic variables essential for integration with the Fuzzy TOPSIS method. Using ordinal descriptors ensures consistency in both the CIB analysis and fuzzy TOPSIS methods, enabling structured evaluation of interactions and their influence on adaptive reuse scenario outcomes.

3.3 STEP 3: IDENTIFY RELATIONSHIPS BETWEEN DESCRIPTORS AND VARIANTS

Identifying the interrelationships between descriptor variants is critical in Cross-Impact Balance (CIB) analysis, as it ensures the logical coherence and plausibility of the scenarios generated (Weimer-Jehle, 2023). These interrelationships capture how one variant influences or is influenced by another, reflecting the underlying dynamics of the system. Without this step, the analysis risks inconsistencies or contradictions, undermining the reliability of the scenarios (Weimer-Jehle, 2023).

To identify these relationships, the scale recommended by (Weimer-Jehle, 2006) provides a structured and systematic approach. This scale uses a range from -3 to +3 to denote the influence of one variant on another: +3 indicates a strong positive impact, 0 signifies no impact, and -3 represents a strong negative impact. These values are assigned within a cross-impact matrix, ensuring all potential interactions are considered (Table 1). This elicitation of data can be conducted in a participatory group setting with stakeholders, fostering collaboration and shared understanding. Alternatively, other methods such as expert surveys (Weimer-Jehle et al., 2012), Delphi techniques (Tori et al., 2023), or literature reviews (Weimer-Jehle, 2023), can be employed to gather the required input systematically. By following this method, the CIB process produces scenarios that are not only internally consistent but also reflective of the real-world, project-specific dynamics among the factors studied (Weimer-Jehle, 2023).

Table 1: Example of a cross-impact balance judgement section

	Political and Community support		
Environmental Impact	High	Medium	Low
Low	3	2	-2
Medium	2	1	-1
High	-3	-1	2
-3 Strongly hindering	0 Neutral		Strongly promoting +3

3.4 STEP 4: CONSTRUCT SCENARIOS

In Cross-Impact Balance (CIB) analysis, constructing scenarios involves generating combinations of descriptor variants and assessing their internal consistency. The consistency of each scenario is determined using the impact sum, which quantifies the cumulative influence of all variants in a scenario on one another (Weimer-Jehle, 2006). This sum, derived from the cross-impact matrix, indicates whether the combination of variants aligns with the specified interdependencies among descriptors. Without considering interdependencies, any combination of descriptor variants could form a scenario. While the CIB methodology tolerates marginal inconsistencies due to the qualitative nature of input data (Weimer-Jehle, 2023), high inconsistency values suggest contradictions, whereas low values indicate internally consistent and plausible scenarios. To determine the acceptable inconsistency threshold the following Equation (1) can be used (Weimer-Jehle, 2023), in which IC_s is the acceptable inconsistency value and n is the number of descriptors:

$$IC_s \approx \frac{1}{2}\sqrt{n-1} \tag{1}$$

The calculation process can be facilitated using the ScenarioWizard software[1], which automates the assessment of consistency across all possible combinations of descriptor variants. The software produces a scenario tableau as an outcome of this calculation. The tableau displays all consistent scenarios, highlighting the selected variants for each descriptor, and serves as input for the decision analysis in Steps 6–10. This structured representation enables researchers and stakeholders to identify and analyse the most plausible scenarios, ensuring that the results are both rigorous and actionable. By employing this method, CIB analysis supports the systematic exploration of potential futures and aids decision-making processes based on robust, internally consistent scenarios.

3.5 STEP 5: DETERMINING THE WEIGHTS OF THE OBJECTIVES

To pick the most appropriate scenario for a project, it is important that the preferences of the stakeholders are reflected in the outcomes of the decision model. The Analytical Hierarchy Process (AHP) is a robust method for multicriteria decision-making that ensures decisions align with stakeholder priorities through a structured stepwise approach. The process begins with pairwise comparisons, where stakeholders evaluate the relative importance of the objectives from step 2, using Saaty's 9-point Likert scale, ranging from equal importance (1) to extreme superiority (9) (Saaty, 1990). These comparisons populate a matrix that reflects the relative weights of each objective, following Equation (2).

$$M = \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & ann \end{bmatrix} \begin{Bmatrix} 1/9 \le a_{i,j} \le 9 \; if \; i \sim j \\ a_{i,j} = 1, \; if \; i = j \end{Bmatrix} \tag{2}$$

Once the matrices are completed, weights are calculated by normalizing the values within each column to reflect the relative importance of the objective. This involves summing the values in each column $\sum a_{kj}$ for $\boldsymbol{n}$, dividing each objective a_{kj} by the total of its column, and then averaging the normalized scores for each row. The weight for each objective, is computed using Equation (3):

$$w_k = \frac{1}{n}\sum_{j=1}^{n}\frac{a_{kj}}{\sum_{i=1}^{n} a_{ij}} \; for \; k = 1,2,3,\ldots,n \tag{3}$$

where n is the number of objectives. This structured normalization process aggregates the scores to derive the final weights, ensuring a systematic approach that integrates both qualitative judgments and quantitative analysis into the decision-making framework.

The AHP then employs the Consistency Ratio (CR) to assess the coherence of decision-makers' judgments. The CR is determined by comparing the Consistency Index (CI) to the Random Index (RI), which represents the average consistency expected by chance for matrices of a given size (Saaty, 1990). If the CR exceeds a commonly accepted threshold, typically 0.10, it signals that the judgments are not adequately consistent and may need to be revised or reevaluated to ensure reliability.

For instance, if a stakeholder considers 'Environmental Impact' more important than: 'Cost', and 'Cost' more important than: 'Social Impact', it is logically expected that 'Environmental Impact' would also be prioritized over 'Social Impact'. The Consistency Ratio (CR) quantifies the coherence of such pairwise comparisons. A CR below 0.10 indicates a satisfactory level of consistency in the judgments, while a CR exceeding 0.10 suggests inconsistencies that require revision. This evaluation should be performed independently for each matrix and stakeholder to ensure precision and reliability

[1] https://www.cross-impact.org/english/CIB_e_ScW.htm

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in the decision-making process. The CR is calculated using Equation (4):

$$CR = \frac{CI}{RI} \quad (4)$$

The Consistency Index (CI) is a key metric in the AHP used to measure the logical coherence of judgments in pairwise comparison matrices, while the Random Index (RI) represents the average CI derived from 500 reciprocal matrices populated with values from Saaty's fundamental 1–9 scale (Saaty, 1990). The RI varies based on the number of criteria in a matrix, as outlined in Table (2). The CI is calculated using Equation (5):

$$CI = \frac{\lambda_{max} - n}{n - 1} \quad (5)$$

where λ_{max} is the maximum eigenvalue of the comparison matrix, and n is the number of objectives. To compute the eigenvalue for a pairwise comparison matrix in AHP, multiply the pairwise comparison matrix M by the priority vector w using Equation (6):

$$M * w = \lambda max * w \quad (6)$$

Here, w represents the normalized priority weights of the criteria. For each row i in the resulting matrix $A * w$ computed by using Equation (7):

$$\lambda_i = \frac{(A * w)_i}{w_i} \quad (7)$$

Where $(A * w)_i$ is the *i-th* element of the resulting vector, and w_i is the *i-th* element of the priority vector. The maximum eigenvalue of the comparison matrix is then calculated by taking the average value of all λ_i, Where n is the number of objectives using Equation (8):

$$\lambda_{max} = \frac{\sum_{i=1}^{n} \lambda_i}{n} \quad (8)$$

The consistency check is essential to ensure that judgments are logically consistent, as inconsistencies can compromise the validity of the decision-making process, leading to unreliable outcomes. This process reinforces robust decision-making by encouraging stakeholders to critically evaluate their judgments, ensuring coherence and reliability throughout the analysis.

Table 2: Random Index (RI) for different numbers of objectives (Saaty, 1990)

Number of criteria	Random Index (RI)
2	0
3	0.58
4	0.90
5	1.12

3.6 STEP 6: CONSTRUCT THE WEIGHTED FUZZY DECISION MATRIX

Following the elicitation of decision-makers' preferences through the AHP method, the subsequent step involves conducting decision analysis utilizing the Fuzzy TOPSIS method. The Fuzzy TOPSIS method is an extension of the traditional Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) that incorporates fuzzy set theory to handle uncertainty and vagueness in decision-making (Chen, 2000). This approach is particularly useful when preferences are expressed in qualitative terms, such as linguistic variables, which are subjective and imprecise by nature, such as with scenarios in the CIB analysis. Fuzzy sets enable the representation of linguistic variables such as "Low," "Medium," and "High" as fuzzy numbers. Among the different forms of fuzzy sets, triangular fuzzy numbers (TFNs) are most commonly used due to their simplicity and computational efficiency (Chen, 2000). A triangular fuzzy number is represented as $\widetilde{A}_{ij} = (l_{ij}, m_{ij}, u_{ij})$ where l is the lower bound, m is the most likely value, and u is the upper bound, forming a triangular membership function. A fuzzy number $\widetilde{A}$ on R is defined as a triangular fuzzy number (TFN) it its membership function $\mu_{\widetilde{A}}(x) : R \to [0,1]$ is expressed as follows in Equation (9):

$$\mu_{\tilde{A}}(x) = \begin{cases} \frac{x-l}{m-l}, & l \le x \le m \\ \frac{u-x}{u-m}, & m \le x \le u \\ 0, & Otherwise \end{cases} \quad (9)$$

To convert linguistic variables into fuzzy numbers, a predefined fuzzy scale should be developed which assigns specific TFNs to each linguistic term based on expert judgment or domain knowledge. This allows qualitative assessments to be transformed into quantitative data that can be processed within the Fuzzy TOPSIS framework, enabling a more nuanced and flexible evaluation of scenarios under uncertainty. A fuzzy scale is employed to transform the qualitative ordinal variants from the consistent scenarios in Step 4 into fuzzy numbers, which are subsequently used to construct the decision matrix.

Following the fuzzification process, construct the fuzzy pairwise decision matrix by first calculating the relative importance of each objective (w_j) following step 5, using Equation (10):

$$\tilde{V} = \tilde{A}_{ij} \times w_j = (l_{ij} * w_j * m_{ij} * w_j * u_{ij} * w_j) \quad (10)$$

The overall weighted fuzzy decision matrix can then be constructed using Equation (11), Where: m is the number of scenarios, and n is the number of objectives.

$$\tilde{V} = \begin{bmatrix} (l_{11} * w_1, m_{11} * w_1, u_{11} * w_1) & \cdots & (l_{1n} * w_n, m_{1n} * w_n, u_{1n} * w_n) \\ \vdots & \ddots & \vdots \\ (l_{m1} * w_1, m_{m1} * w_1, u_{m1} * w_1) & \cdots & (l_{mn} * w_n, m_{mn} * w_n, u_{mn} * w_n) \end{bmatrix} \quad (11)$$

3.7 STEP 7: NORMALIZE THE WEIGHTED FUZZY DECISION MATRIX

To normalize the weighted fuzzy decision matrix $\widetilde{V}$, each objective $\widetilde{V}_{ij} = (l_{ij}, m_{ij}, u_{ij})$ is normalized based on the type of objective (benefit or cost).

For benefit objectives (higher values are preferred) Equation (12) can be used:

$$\tilde{R}_{ij} = (\frac{l_{ij}}{u_j}, \frac{m_{ij}}{u_j}, \frac{u_{ij}}{u_j}) \qquad (12)$$

For the cost criteria (lower values are preferred) Equation (13) is used:

$$\tilde{R}_{ij} = (\frac{l_j^-}{u_{ij}}, \frac{m_j^-}{m_{ij}}, \frac{u_j^-}{l_{ij}}) \qquad (13)$$

Where u_j^+ is the maximum upper bound for the $j-th$ objective, and l_j^- is het minimum lower bound for the $j-th$ objective.

3.8 STEP 8: DETERMINE THE FUZZY POSITIVE-IDEAL SOLUTION (FPIS) AND FUZZY NEGATIVE-IDEAL SOLUTION (FNIS)

In the Fuzzy TOPSIS method, the FPIS (Fuzzy Positive Ideal Solution) represents the optimal fuzzy values for each objective, while the FNIS (Fuzzy Negative Ideal Solution) reflects the least desirable outcomes. These are determined by identifying the best and worst fuzzy scores across all scenarios for each objective. Scenarios are ranked based on their proximity to the FPIS and distance from the FNIS, with the closest scenario to the FPIS and farthest from the FNIS considered the best choice.

If x_{ij} represents the fuzzy evaluation of the i-th alternative with respect to the j-th objective, the FPIS for each criterion can be represented as:

$$A_j^* = \begin{cases} max_i x_{ij} \text{ } if \text{ } the \text{ } objective \text{ } is \text{ } beneficial \\ min_i x_{ij} \text{ } if \text{ } the \text{ } objective \text{ } is \text{ } non-beneficial \end{cases} \qquad (14)$$

Conversely, If x_{ij} represents the fuzzy evaluation of the i-th alternative with respect to the j-th objective, the FNIS for each objective can be represented as:

$$A_j^- = \begin{cases} min_i x_{ij} \text{ } if \text{ } the \text{ } objective \text{ } is \text{ } beneficial \\ max_i x_{ij} \text{ } if \text{ } the \text{ } objective \text{ } is \text{ } non-beneficial \end{cases} \qquad (15)$$

3.9 STEP 9: CALCULATE THE DISTANCE OF EACH SCENARIO FROM FPIS AND FNIS

The distances from each scenario to the FPIS (d_i^*) and FNIS (d_i^-) are calculated using the fuzzy distance measure: Euclidian distance using Equation (16).

The distance d between two fuzzy numbers $\widetilde{A}_1 = (l_1, m_1, u_1)$ and $\widetilde{A}_2 = (l_2, m_2, u_2)$ is:

$$d(\tilde{A}_1, \tilde{A}_2) = \sqrt{\frac{1}{3} = [(l_1 - l_2)^2 + (m_1 - m_2)^2 + (u_1 - u_2)^2]} \qquad (16)$$

To calculate the distances from FPIS and FNIS to each scenario the following Equations (17&18) can be used:

Distance from FPIS:

$$(d_i^+): \ d_i^+ \sqrt{\sum_{j=1}^{n} (\tilde{R}_{ij} - \tilde{A}_j^+)^2} \qquad (17)$$

Distance from FNIS

$$(d_i^-): d_i^- \sqrt{\sum_{j=1}^{n} (\tilde{R}_{ij} - \tilde{A}_j^-)^2} \qquad (18)$$

Here, *n* is the number of objectives, x_{ij} is the fuzzy score of the *i-th* scenario on the *j-th* objective, and A_j^+ is the score of the FPIS on the *j-th* objective, and A_j^- is the score of the FNIS on the *j-th* objective. Using these distances, each scenario's relative closeness to the ideal solution is calculated, which is used to rank the scenarios. The alternative with the shortest distance to the FPIS and the longest distance from the FNIS is considered the optimal choice.

3.10 STEP 10: OBTAIN THE CLOSENESS COEFFICIENTS OF EACH SCENARIO

In the Fuzzy TOPSIS method, the closeness indicator is a metric for ranking scenarios by measuring their proximity to the Fuzzy Positive Ideal Solution (FPIS) and their distance from the Fuzzy Negative Ideal Solution (FNIS). This ranking provides decision makers with a clear understanding of which scenario best aligns with their preferences and objectives. By summarizing each scenario's performance across all objectives, the closeness indicator supports informed, consensus-driven decisions, highlighting not only the best options but also how closely each one approaches the ideal conditions. The closeness indicator is calculated by using the following Equation (19):

$$CC_i = \frac{d_i^-}{d_i^+ + d_i^-} \qquad (19)$$

Where $\boldsymbol{d_i^+}$ is the distance of the *i-th* alternative from the FPIS, and $\boldsymbol{d_i^-}$ is its distance from the FNIS. The closeness indicator, $\boldsymbol{CC_i}$, ranges from 0 to 1, where a value closer to 1 indicates that the scenario is closer to the FPIS and farther from the FNIS, making it a more preferable option.

4 HYPOTHETICAL EXAMPLE

The application of the newly introduced mixed-method approach is demonstrated using a hypothetical example of an adaptive reuse project.

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4.1 STEP 1: DEFINE THE AIM AND OBJECTIVES

For the hypothetical example we have developed the following aim, objectives and criteria. For the selection of the objectives and criteria we have drawn inspiration from van Laar et al., (2024), who conducted an extensive literature review on criteria and objectives in the decision-making process of adaptive reuse. For practical reasons we have limited the number of objectives to five.

Table 3: The project aim and objectives of the hypothetical example

Project Aim	The aim of this project is to adaptively reuse an existing building to meet functional, environmental, and social needs while preserving its historical, significance.
Objectives	O1) To increase social impact O2) To reduce environmental impact O3) To reduce cost O4) To improve the physical quality and durability of the building O5) To preserve the historic and cultural value of the building

4.2 STEP 2: DEVELOP DESCRIPTORS AND VARIANTS

Based on the objectives chosen, comprehensive descriptors and variants were developed that included names, description, objective and criteria (Appendix A). For all descriptors, 3 ordinal variants were drawn up: a strong variant in which the objective within the descriptor is definitely reached, a medium variant in which the objective is partially reached, and a weak variant in which the objective is not reached.

The same linguistic variables were chosen for each objective to simplify the FUZZY translation in Step 6.

An example for the descriptor Social impact is provided in Table (4).

Table 4: The descriptor: "Social Impact" and its corresponding variants

Descriptor: Social Impact		**Variants**
Objective	To increase social Impact	**A1: Social Heaven (strong variant)** The adaptive reuse project enhances social impact by addressing socio-economic factors like house prices, gentrification, and perceived safety while boosting neighbourhood liveability. It fosters social cohesion by serving as a community hub and improves surrounding public spaces.
Criteria	Social cohesion Public spaces Liveability Socio-economic conditions	**A2: Socially Acceptable (medium variant)** The adaptive reuse project avoids negative socio-economic impacts, with some focus on enhancing public spaces and liveability. While not central to fostering community, it offers spaces for social interaction. **A3: Socially Limited (weak variant)** The adaptive reuse project negatively impacts socio-economic conditions, potentially raising housing prices and driving gentrification. It fails to improve liveability, public spaces, or social cohesion.

4.3 STEP 3: IDENTIFY RELATIONSHIPS BETWEEN DESCRIPTORS AND VARIANTS

We have mapped the interactions between all descriptor-variant combinations using the scale from Weimer-Jehle, (2006). This resulted in the following Cross-impact balance matrix (Table 5):

Table 5: The completed CIB matrix for the hypothetical example

CIB Matrix	**A) Social Impact**			**B) Environmental Impact**			**C) Cost**			**D) Physical quality**			**E) Historic and Cultural value**		
	A1	A2	A3	B1	B2	B3	C1	C2	C3	D1	D2	D3	E1	E2	E3
A) Social Impact:															
A1) Social heaven				3	2	-2	1	0	0	0	0	0	3	2	-2
A2) Socially acceptable				2	1	-1	0	0	0	0	0	0	2	1	-1
A3) Socially limited				-2	-1	2	-1	0	1	0	0	0	-2	0	2
B) Environmental Impact:															
B1) Sustainability heaven	2	1	0				-3	-1	3	0	0	0	0	-1	0
B2) Environmentally friendly	0	0	0				-1	0	1	0	0	0	1	1	-1
B3) Environmentally unfriendly	-2	-1	1				-1	1	-1	0	0	0	1	0	0
C) Cost:															
C1) Cost Efficient	1	1	-1	-1	2	1				3	2	1	-2	-1	2
C2) Moderately costly	0	0	0	-1	2	1				1	0	-1	1	1	0
C3) Very costly	-2	-1	1	2	-2	2				2	1	-2	-3	-1	3
D) Physical quality:															
D1) Strong and Durable	1	0	0	3	2	0	2	-1	-2				3	2	-2
D2) Sufficiently durable	0	0	0	2	1	0	1	1	-1				2	1	0
D3) Poor building quality	0	0	1	-2	0	1	-2	1	2				-3	-1	2
E) Historic/Cultural value															
E1) Preserving History	2	1	-1	-1	0	0	-2	-1	2	3	2	-2			
E2) Attention to history	1	0	0	0	0	0	-1	0	1	2	1	-1			
E3) Ignoring history	-2	-1	2	1	0	0	1	0	-1	-1	0	2			
Impact Sum	6	3	-2	4	6	-1	-2	-3	3	6	4	-1	4	2	-2

4.4 STEP 4: CONSTRUCT SCENARIOS

The consistency analysis was performed using the ScenarioWizard software, with a consistency value of 1 following Equation (1). This resulted in 4 consistent scenarios that are included for decision analysis (Figure 2). Each scenario consists of a consistent combination of variants that is characterised by strong (green), medium (yellow), or weak (red) in relation to the objective of the descriptor.

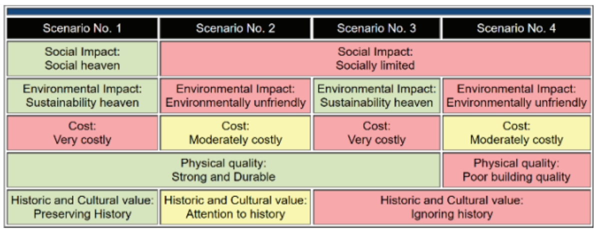

Figure 2: The scenario tableau for the hypothetical example

4.5 STEP 5: DETERMINING THE WEIGHTS OF THE OBJECTIVES

We determined the weights of the objectives through the AHP methodology by using the Saaty's 9-point Likert scale (Saaty, 1990). The relative importance of the objectives is displayed in the pairwise comparison matrix:

$$
M = \begin{array}{c} \\ O_1 \\ O_2 \\ O_3 \\ O_4 \\ O_5 \end{array} \begin{bmatrix} O_1 & O_2 & O_3 & O_4 & O_5 \\ 1 & (3) & (5) & (7) & (9) \\ (0.33) & 1 & (3) & (5) & (7) \\ (0.2) & (0.33) & 1 & (3) & (5) \\ (0.14) & (0.2) & (0.33) & 1 & (3) \\ (0.11) & (0.14) & (0.2) & (0.33) & 1 \end{bmatrix} \quad (20)
$$

The pairwise comparison matrix was normalized by dividing each entry by the sum of its column using Equation (3), which results in the normalized pairwise comparison matrix: Equation (21).

$$
M_n = \begin{array}{c} \\ O_1 \\ O_2 \\ O_3 \\ O_4 \\ O_5 \end{array} \begin{bmatrix} O_1 & O_2 & O_3 & O_4 & O_5 \\ (0.520) & (0.545) & (0.476) & (0.437) & (0.400) \\ (0.173) & (0.182) & (0.286) & (0.312) & (0.311) \\ (0.104) & (0.061) & (0.095) & (0.188) & (0.222) \\ (0.073) & (0.036) & (0.032) & (0.062) & (0.133) \\ (0.057) & (0.027) & (0.019) & (0.041) & (0.089) \end{bmatrix} \quad (21)
$$

The relative weight w_k of each objective was calculated by averaging the normalized values across each row. Table (6). presents the final weights. The objective "To reduce cost" is the most important, while the objective "To increase social impact" is the least important.

Table 6: The weights for each objective following AHP

Objective (O_n)	Weight (w_k)
To reduce cost (O_3)	0.476
To preserve the historic & cultural value of the building (O_5)	0.253
To improve the physical quality/ durability of the building (O_4)	0.134
To reduce environmental impact (O_2)	0.067
To increase social impact (O_1)	0.045

To ensure the judgments were consistent, the largest eigenvalue was computed using Equation (22) along with the Consistency Index (CI); Equation (23) and Consistency Ratio (CR); Equation (24):

Largest Eigenvalue:

$$
\lambda_{max} = \frac{\lambda_1 + \lambda_2 + \lambda_3 + \lambda_4 + \lambda_5}{5} = \lambda_{max} = \frac{5.83 + 5.78 + 5.51 + 5.42 + 4.07}{5} = 5.333 \quad (22)
$$

Consistency Index (CI):

$$
CI = \frac{\lambda_{max} - n}{n - 1} = \frac{5.333 - 5}{5 - 1} = 0.083 \quad (23)
$$

The Random Index (RI) value with 5 objectives is: 1.12 (Table 2).

Consistency Ratio (CR)

$$
CR = \frac{CI}{RI} = \frac{0.083}{1.12} = 0.074 \quad (24)
$$

The Consistency Ratio (CR) = 0.074 is below the threshold of 0.1, indicating that the pairwise comparison matrix is acceptably consistent.

4.6 STEP 6: CONSTRUCT THE WEIGHTED FUZZY DECISION MATRIX

The decision matrix D with linguistic variables is constructed based on the outcome of the consistency analysis from Step 4 (Figure 2), with S_n being the scenarios; Equation (25).

$$
D = \begin{array}{c} \\ O_1 \\ O_2 \\ O_3 \\ O_4 \\ O_5 \end{array} \begin{bmatrix} S_1 & S_2 & S_3 & S_4 \\ Strong & Weak & Weak & Weak \\ Strong & Weak & Strong & Weak \\ Weak & Medium & Weak & Medium \\ Strong & Strong & Strong & Weak \\ Strong & Medium & Weak & Weak \end{bmatrix} \quad (25)
$$

To transform the linguistic decision matrix into a fuzzy matrix, the following conversion scale is used that incorporates triangular fuzzy numbers (Table 7).

Table 7: The linguistic variable conversion table

Linguistic variable	Corresponding triangular fuzzy numbers (l, m, u)
Weak	(1,3,5)
Medium	(3,5,7)
Strong	(5,7,9)

After conversion the following fuzzy decision matrix D_f was constructed using Equation (26):

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$$D_f = \begin{array}{c} \\ O_1 \\ O_2 \\ O_3 \\ O_4 \\ O_5 \end{array} \begin{bmatrix} S_1 & S_2 & S_3 & S_4 \\ (5,7,9) & (1,3,5) & (1,3,5) & (1,3,5) \\ (5,7,9) & (1,3,5) & (5,7,9) & (1,3,5) \\ (1,3,5) & (3,5,7) & (1,3,5) & (3,5,7) \\ (5,7,9) & (5,7,9) & (5,7,9) & (1,3,5) \\ (5,7,9) & (3,5,7) & (1,3,5) & (1,3,5) \end{bmatrix} \quad (26)$$

To arrive at the weighted fuzzy decision matrix the relative weights of the objectives w_k were multiplied with the triangular fuzzy numbers (Table 8):

4.7 STEP 7: NORMALIZE THE WEIGHTED FUZZY DECISION MATRIX

Using Equation (12) we can then normalize the weighted fuzzy decision matrix (Table 9).

Table 8: The weighted fuzzy decision matrix for the hypothetical example

	Scenario 1 (S_1)	Scenario 2 (S_2)	Scenario 3 (S_3)	Scenario 4 (S_4)
Social Impact (O_1)	(0.225, 0.315, 0.405)	(0.045, 0.135, 0.225)	(0.045, 0.135, 0.225)	(0.045, 0.135, 0.225)
Environmental impact (O_2)	(0.335, 0.469, 0.603)	(0.067, 0.201, 0.335)	(0.335, 0.469, 0.603)	(0.067, 0.201, 0.335)
Cost (O_3)	(0.476, 1.428, 2.380)	(1.428, 2.380, 3.332)	(0.476, 1.428, 2.380)	(1.428, 2.380, 3.332)
Physical quality (O_4)	(0.670, 0.938, 1.206)	(0.670, 0.938, 1.206)	(0.670, 0.938, 1.206)	(0.134, 0.402, 0.670)
Historic/ cultural value (O_5)	(1.265, 1.771, 2.277)	(0.759, 1.265, 1.771)	(0.253, 0.759, 1.265)	(0.253, 0.759, 1.265)

Table 9: The normalized weighted fuzzy decision matrix for the hypothetical example

	Scenario 1 (S_1)	Scenario 2 (S_2)	Scenario 3 (S_3)	Scenario 4 (S_4)
Social Impact (O_1)	(0.095, 0.132, 0.170)	(0.014, 0.041, 0.068)	(0.019, 0.057, 0.095)	(0.014, 0.041, 0.068)
Environmental impact (O_2)	(0.141, 0.197, 0.253)	(0.020, 0.060, 0.101)	(0.141, 0.197, 0.253)	(0.020, 0.060, 0.101)
Cost (O_3)	(0.200, 0.600, 1.000)	(0.429, 0.714, 1.000)	(0.200, 0.600, 1.000)	(0.429, 0.714, 1.000)
Physical quality (O_4)	(0.282, 0.394, 0.507)	(0.201, 0.282, 0.362)	(0.282, 0.394, 0.507)	(0.040, 0.121, 0.201)
Historic/ cultural value (O_5)	(0.532, 0.744, 0.957)	(0.228, 0.380, 0.532)	(0.106, 0.319, 0.532)	(0.076, 0.228, 0.380)

4.8 STEP 8: DETERMINE THE FUZZY POSITIVE-IDEAL SOLUTION (FPIS) AND FUZZY NEGATIVE-IDEAL SOLUTION (FNIS)

Using the normalized weighted fuzzy decision matrix from Step 7 (Table 9), the FPIS and FNIS were calculated for each objective using Equation 14 and 15 resulting in Table (10).

Table 10: The FPIS and FNIS values for each objective in the hypothetical example

Objectives (O_n)	FPIS	FNIS
Social Impact (O_1)	(0.095, 0.132, 0.170)	(0.014, 0.041, 0.068)
Environmental impact (O_2)	(0.141, 0.197, 0.253)	(0.020, 0.060, 0.101)
Cost (O_3)	(0.429, 0.714, 1.000)	(0.200, 0.600, 1.000)
Physical quality (O_4)	(0.282, 0.394, 0.507)	(0.040, 0.121, 0.201)
Historic/ cultural value (O_5)	(0.532, 0.744, 0.957)	(0.076, 0.228, 0.380)

4.9 STEP 9: CALCULATE THE DISTANCE OF EACH SCENARIO FROM FPIS AND FNIS

Using the Euclidean distance each scenario from the FPIS and FNIS were computed using Equation (16). Distances were calculated for each scenario based on the FPIS $D^+$and FNIS D^- (Table 11).

Table 11: The distance from each scenario to the FPIS and FNIS

Scenario (S_n)	D^+ (FPIS Distance)	D^- ($FNIS\ Distance$)
Scenario 1 (S_1)	0.543	0.802
Scenario 2 (S_2)	0.786	0.617
Scenario 3 (S_3)	0.643	0.732
Scenario 4 (S_4)	0.849	0.503

4.10 STEP 10: OBTAIN THE CLOSENESS COEFFICIENTS OF EACH SCENARIO

Once the distances from FPIS and FNIS are determined, the Closeness Coefficients can be obtained using Equation (27). An example calculation for Scenario 2 is given:

$$CC_i = \frac{d_i^-}{d_i^+ + d_i^-} = \frac{0.617}{0.786 + 0.617} = 0.440 \quad (27)$$

This results in the following scenario ranking, with scenario 1 ultimately ranking on top (Table 12).

Table 12: The Closeness Coefficient for each scenario

Scenario (S_n)	Closeness Coëfficiënt CC_n	Rank
Scenario 1 (S_1)	0.596	1
Scenario 2 (S_2)	0.440	3
Scenario 3 (S_3)	0.532	2
Scenario 4 (S_4)	0.372	4

5 CONCLUSION AND REMARKS

This study has introduced an integrated decision-making framework that combines Cross-Impact Balance (CIB) analysis, the Analytic Hierarchy Process (AHP), and Fuzzy-TOPSIS to enhance scenario development and multi-criteria evaluation in adaptive reuse projects. By incorporating scenario-based methodologies within a structured decision-making process, this approach enables stakeholders to systematically explore future-oriented reuse options while addressing uncertainty, complexity, and competing priorities. The framework was demonstrated through a hypothetical adaptive reuse project, illustrating how these methods interact to generate, assess, and rank consistent scenarios.

The findings highlight the benefits of integrating different methodologies to strengthen decision-making. CIB analysis ensures scenario consistency, reducing the likelihood of incoherent or contradictory planning outcomes. AHP provides a structured means to weight stakeholder preferences, ensuring that diverse perspectives are reflected in the evaluation process. Meanwhile, Fuzzy-TOPSIS offers a robust ranking mechanism that accounts for uncertainty, allowing decision-makers to prioritize alternatives more effectively. The integration of these methods enhances future-oriented decision-making by ensuring that adaptive reuse strategies consider long-term sustainability, economic feasibility, and social impact rather than being constrained by immediate limitations. Additionally, the approach fosters stakeholder engagement and transparency by actively involving participants in defining objectives, developing descriptors, and evaluating scenarios, leading to a more inclusive and aligned decision-making process. The structured methodology also enhances practical applicability, making it adaptable for real-world projects where trade-offs must be assessed, and priorities established.

Despite its advantages, certain limitations should be acknowledged. The methodology relies significantly on subjective inputs, particularly in scenario development and the conversion of linguistic variables in the Fuzzy-TOPSIS method. Its effectiveness depends on the ability of stakeholders and experts to define meaningful descriptors and variants, assess interactions accurately, and translate qualitative insights into quantitative measures. Any inconsistencies or biases in these subjective judgments could influence the final rankings. Moreover, for the methodology to function effectively, it is crucial to ensure active stakeholder participation at multiple stages, including defining objectives, developing scenario descriptors, weighting criteria, and ranking scenarios. Without sufficient engagement, the approach risks overlooking critical real-world considerations and diminishing the legitimacy of its outcomes. Future research should explore participatory mechanisms to strengthen stakeholder involvement and ensure a balanced representation of perspectives.

5.1 FUTURE RESEARCH DIRECTIONS

To further validate the proposed approach, real-world case studies should be conducted to test its practical applicability. Future research could also focus on:

- Improving the linguistic variable conversion process by developing standardized fuzzy scales that minimize subjectivity.
- Automating parts of the methodology to reduce the complexity of data input and improve usability.
- Exploring hybrid decision-support tools that integrate participatory scenario development with computational methods to enhance consistency and scalability.

The proposed framework demonstrates the potential of integrating scenario planning and multi-criteria decision-making, yet its full impact can only be realized through real-world applications. As the built environment continues to evolve, future efforts should focus on refining participatory methods and optimizing decision-support tools to promote practical applicability, ensuring that adaptive reuse strategies are data-driven, inclusive, and aligned with long-term sustainability goals.

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