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Evaluation of Cutting-Edge Technologies for Economic Growth through Fuzzy AHP Approach

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Abstract: In the modern global economy, sustainability has emerged as a crucial foundation for achieving long-term stability and growth. Escalating environmental challenges, depletion of natural resources, and growing social expectations have made the selection of suitable technologies and innovations essential for sustainable economic progress. Yet, such decisions are often made amid uncertainty driven by technological risks, volatile markets, evolving regulations, and geopolitical instability. These factors complicate decision-making for policymakers, industry leaders, and investors, underscoring the need for resilient analytical frameworks that support informed innovative choices while mitigating risks. Achieving harmony between innovation and sustainability requires balancing economic feasibility, environmental responsibility, and social well-being. This study introduces a holistic framework for evaluating advanced technologies that contribute to economic development under uncertain and complex conditions. Utilizing the fuzzy Analytic Hierarchy Process (AHP) with Z numbers, the approach combines fuzzy logic and Z-numbers to effectively represent uncertainty and the reliability of expert evaluations. The model supports a structured multi-criteria assessment that integrates economic, environmental, and social dimensions, guiding stakeholders in selecting technologies that foster sustainable and adaptable growth. Through conceptual analysis and practical case applications, the research validates the efficiency of the fuzzy Z-AHP approach as a robust, transparent, and flexible decision-making tool for technology evaluation in dynamic economic environments. The outcomes enhance methodological advancement in sustainable development and strategic innovation management.

Index Terms: Fuzzy AHP, Z-numbers, Multi-Criteria Decision-Making, Advanced Technology Evaluation

1. Introduction

In the modern era of rapid technological progress and complex economic dynamics, sustainable economic growth increasingly relies on the integration of advanced technologies. However, the volatile and unpredictable nature of global markets introduces significant uncertainty, complicating strategic planning and decision-making processes. Traditional quantitative models often fall short in capturing the ambiguity inherent in such conditions. To address these limitations, Z-numbers, an advanced mathematical tool that accounts for both uncertainty and the degree of confidence, have gained prominence as a powerful analytical approach. By merging innovative technologies with refined methods of uncertainty analysis, this research seeks to provide a deeper understanding of how economies can navigate instability and harness technological advancements to foster sustainable development. The interaction between advanced technologies and economic growth has become a central theme in both academic and policy discourse in this century. Growing global instability driven by geopolitical conflicts, financial fluctuations, pandemics, climate crises, and rapid technological disruption has intensified the focus on the role of emerging technologies in shaping economic resilience. Contemporary studies increasingly explore not only the potential of technologies to drive growth but also their reliability in volatile, uncertain, complex, and ambiguous environments. Consequently, evaluating the contribution of advanced technologies under uncertainty has become an essential yet challenging research objective. Many scholars highlight the dual nature of uncertainty in development: as an external constraint (e.g., market volatility, supply chain disruptions) and as an inherent characteristic of technological innovation itself. Emerging technologies such as artificial intelligence, blockchain, quantum computing, and biotechnology evolve at a pace that often surpasses existing policies, institutional capacities, and societal comprehension [1]. Theoretical frameworks rooted in systems theory and evolutionary economics therefore emphasize adaptability and resilience rather than mere efficiency [2]. These perspectives suggest that technology adoption should be seen as a continuous, adaptive process involving feedback, learning, and institutional co-evolution. For instance, studies on AI in developing economies show that success depends not only on access to technology but also on responsive governance, skilled labor, and flexible regulatory systems. Similarly, research on digital transformation during the pandemic demonstrates that digital tools sustained economic activity only when institutions exhibited agility and inclusiveness. Technological readiness under conditions of uncertainty has become another key research focus [3]. Readiness now extends beyond technical infrastructure to encompass broader socio-economic adaptability. Technological progress often benefits regions and organizations already equipped with resources, skills, and institutional support, while those lacking such assets risk being left further behind. To analyze technology's impact on development amid uncertainty, scholars have increasingly turned to innovative methodological frameworks [4]. Scenario analysis and foresight studies have become increasingly important for exploring possible futures shaped by technological innovation and systemic risks. These approaches allow researchers and policymakers to evaluate how varying levels of technology adoption or policy choices might unfold under different global scenarios. In parallel, complexity theory has been employed to investigate nonlinear interactions, feedback mechanisms, and emergent patterns within technology-driven economies. Such frameworks are especially valuable when traditional forecasting, reliant on historical data, fails to capture the uncertainty of modern environments. The potential of advanced technologies such as automation, artificial intelligence, big data analytics, the Internet of Things, and blockchain to stimulate economic growth is widely recognized. Nevertheless, their actual impact remains inconsistent, as implementation is often constrained by uncertainties related to data accuracy, expert judgments, source reliability, and environmental volatility. Consequently, researchers increasingly seek analytical tools capable of evaluating how these technologies influence economic development under uncertain conditions. Within this context, Z-numbers introduced by Lotfi Zadeh have emerged as a powerful methodological framework for representing both the fuzziness of information and the confidence associated with it [5]. Recent studies have begun to integrate Z-number modeling with assessments of advanced technologies, providing promising yet still evolving analytical structures [6]. Z-numbers have also proven effective in decision-making models that deal directly with uncertainty management [7]. For example, in project risk assessment, where both the likelihood and consequence of risks carry varying degrees of reliability, Z-number-based models yield more refined evaluations than conventional fuzzy or probabilistic methods [8]. Similarly, in evaluating information technology for warehouse order picking, fuzzy multicriteria decision-making models using Z-numbers enable expert assessments to reflect both uncertainty and confidence levels [9]. Multicriteria decision-making remains the primary domain for the application of Z-numbers in studies related to technology and economic development [10]. When evaluating alternatives, whether technologies, policies, or strategic options under uncertain conditions, decision-makers must balance multiple factors such as cost, performance, risk, infrastructure, and social acceptance [11]. Z-numbers provide a structured way to address two key dimensions of uncertainty: the estimated value of each criterion and the decision-maker's confidence in that estimate [12]. Incorporating reliability into the assessment of advanced technologies is now seen as essential in dynamic and uncertain environments. Scholars emphasize that neglecting reliability can lead to overconfidence or misjudgment, while accounting for it produces more balanced and realistic evaluations [13]. Empirical research further supports this view, showing that models using Z-numbers generally outperform those relying solely on fuzzy or crisp values, especially when data are incomplete or imprecise. This article investigates how advanced technologies contribute to economic development under uncertainty through the application of Z-numbers. In this study, extended the traditional fuzzy AHP framework by integrating a modified Z-number approach that captures both uncertainty and reliability of expert judgments more effectively. Unlike conventional methods, the proposed methodology introduces a new aggregation operator for Z-numbers, which reduces information loss when combining multiple expert opinions and enhances the consistency of the decision-making process. This hybrid approach not only provides a more robust theoretical foundation for handling uncertain and imprecise information but also demonstrates practical applicability through a case study in evaluation of cutting-edge technologies for economic growth, where existing methods have shown limitations. This framework can be further extended to incorporate real-time data and adaptive decision-making, allowing dynamic updates to rankings. Future research could also explore integration with machine learning models to estimate Z-number parameters from large datasets, reducing reliance on subjective expert judgments. The structure of the paper is as follows: section 2 introduces the core definitions of the dynamic fuzzy multi-attribute decision-making approach using Z-numbers, section 3 details the formulation and solution of the technology evaluation problem, and section 3 presents the study's main findings.

2. Preliminaries

Definition 1. Mathematical models that combine linguistic variables with standard arithmetic operations form the basis of the algebra of fuzzy numbers. In many decision-making contexts, experts express their assessments using imprecise terms like "approximately 0," "close to 1," or "around 10," which correspond to fuzzy numbers. Among the different types, triangular fuzzy numbers are the most used in practical applications. A triangular fuzzy number graphical depiction is illustrated in Fig. 1.

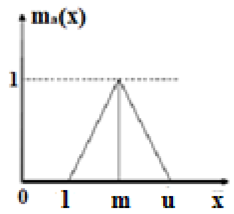

Fig. 1. Illustration of a triangular fuzzy number

The membership function of a triangular fuzzy number (TFN) is usually defined in a piecewise linear form. Let a triangular fuzzy number be denoted as

$$\tilde{A} = (l, m, u) \tag{1}$$

where, l is the lower bound (minimum value), m is the modal value (most likely), u is the upper bound (maximum value). The membership function $\mu_{\tilde{A}}(x)$is defined as:

$$\mu_{\tilde{A}}(x) = \begin{cases} 0, & x < l \\ \frac{x-l}{m-l}, & l \le x \le m \\ \frac{u-x}{u-m}, & m \le x \le u \\ 0, & x > u \end{cases} \tag{2}$$

For $x < l$or $x > u$, the membership is 0 (outside the range). Between $l$and m, membership increases linearly from 0 to 1. Between $m$and u, membership decreases linearly from 1 to 0.

Definition 2. Let $\tilde{X} = (l_X, m_X, u_X)$ and $\tilde{Y} = (l_Y, m_Y, u_Y)$ be triangular fuzzy numbers. The basic arithmetic operations are defined as follows:

1. Addition

$$\tilde{X} + \tilde{Y} = (l_X + l_Y,\ m_X + m_Y,\ u_X + u_Y) \tag{3}$$

2. Subtraction

$$\tilde{X} - \tilde{Y} = (l_X - u_Y,\ m_X - m_Y,\ u_X - l_Y) \tag{4}$$

3. Multiplication

$$\tilde{X} \times \tilde{Y} = (\min(l_X l_Y, l_X u_Y, u_X l_Y, u_X u_Y),\ m_X m_Y,\ \max(l_X l_Y, l_X u_Y, u_X l_Y, u_X u_Y)) \tag{5}$$

4. Division

$$\tilde{X} \div \tilde{Y} = (\min(l_X/l_Y, l_X/u_Y, u_X/l_Y, u_X/u_Y),\ m_X/m_Y,\ \max(l_X/l_Y, l_X/u_Y, u_X/l_Y, u_X/u_Y)), 0 \notin [l_Y, u_Y] \tag{6}$$

5. Scalar multiplication (for a positive scalar $k > 0$)

$$k \cdot \tilde{X} = (k \cdot l_X,\ k \cdot m_X,\ k \cdot u_X) \tag{7}$$

Addition and scalar multiplication are straightforward, component-wise. Subtraction and division consider the extreme values of the triangular numbers to preserve the fuzzy interval. Multiplication and division take the minimum and maximum of all possible combinations of bounds to ensure the result covers all possibilities.

These operations are fundamental in fuzzy AHP computations, including the transformation of Z-numbers and the aggregation of pairwise comparisons.

Definition 3. Z-numbers are represented using triangular fuzzy numbers (TFNs) to capture both the evaluation and reliability components. Let a Z-number be denoted as

$$Z = (\tilde{A}, \tilde{B}) \tag{8}$$

where $\tilde{A} = (l_A, m_A, u_A)$ is the fuzzy restriction representing the estimated value, and $\tilde{B} = (l_B, m_B, u_B)$ is the fuzzy reliability representing the confidence in that evaluation [14]. The membership function of each triangular fuzzy number is defined as:

$$\mu_{\tilde{A}}(x) = \begin{cases} 0, & x < l_A, \\ \frac{x - l_A}{m_A - l_A}, & l_A \le x \le m_A, \\ \frac{u_A - x}{u_A - m_A}, & m_A \le x \le u_A, \\ 0, & x > u_A, \end{cases} \quad \mu_{\tilde{B}}(y) = \begin{cases} 0, & y < l_B, \\ \frac{y - l_B}{m_B - l_B}, & l_B \le y \le m_B, \\ \frac{u_B - y}{u_B - m_B}, & m_B \le y \le u_B, \\ 0, & y > u_B. \end{cases} \tag{9}$$

To integrate Z-numbers into fuzzy AHP, the reliability component $\tilde{B}$ is first defuzzified using the centroid method:

$$\alpha = \frac{l_B + m_B + u_B}{3} \tag{10}$$

The equivalent weighted fuzzy restriction is then computed as:

$$\tilde{A}_{eq} = \alpha \cdot \tilde{A} = (\alpha \cdot l_A,\ \alpha \cdot m_A,\ \alpha \cdot u_A) \tag{11}$$

This produces a single triangular fuzzy number $\tilde{A}_{eq}$that incorporates both the original evaluation and the expert's confidence, enabling it to be directly used in further calculations.

Definition 4. Operations on Z-numbers represented as TFNs. Let $Z_1 = (\tilde{A}_1, \tilde{B}_1)$ and $Z_2 = (\tilde{A}_2, \tilde{B}_2)$ be two Z-numbers with triangular fuzzy number components. After transforming Z-numbers into equivalent TFNs $\tilde{A}_{1,eq}$ and $\tilde{A}_{2,eq}$, standard fuzzy number operations can be applied [15]:

1. Addition

$$Z_1 + Z_2 = \tilde{A}_{1,eq} + \tilde{A}_{2,eq} = (l_1 + l_2,\ m_1 + m_2,\ u_1 + u_2) \tag{12}$$

2. Subtraction

$$Z_1 - Z_2 = \tilde{A}_{1,eq} - \tilde{A}_{2,eq} = (l_1 - u_2,\ m_1 - m_2,\ u_1 - l_2) \tag{13}$$

3. Multiplication

$$Z_1 \times Z_2 = \tilde{A}_{1,eq} \times \tilde{A}_{2,eq} = (\min(l_1 l_2, l_1 u_2, u_1 l_2, u_1 u_2),\ m_1 m_2,\ \max(l_1 l_2, l_1 u_2, u_1 l_2, u_1 u_2)) \tag{14}$$

4. Division

$$Z_1 \div Z_2 = \tilde{A}_{1,eq} \div \tilde{A}_{2,eq} = (\min(l_1/l_2, l_1/u_2, u_1/l_2, u_1/u_2),\ m_1/m_2,\ \max(l_1/l_2, l_1/u_2, u_1/l_2, u_1/u_2)), 0 \notin [l_2, u_2] \tag{15}$$

Definition 5. In the fuzzy AHP framework with Z-numbers, the comparison matrix is a square matrix in which each element represents the relative importance of one criterion (or alternative) compared to another. When using Z-numbers, each element of the matrix captures not only the expert evaluation but also the confidence associated with that evaluation. Let the set of criteria be

$$C = \{C_1, C_2, \ldots, C_n\} \tag{16}$$

The Z-number pairwise comparison matrix is defined as

$$\mathrm{Z} = \begin{bmatrix} Z_{11} & Z_{12} & \cdots & Z_{1n} \\ Z_{21} & Z_{22} & \cdots & Z_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ Z_{n1} & Z_{n2} & \cdots & Z_{nn} \end{bmatrix} \tag{17}$$

where each element

$$Z_{ij} = (\tilde{A}_{ij}, \tilde{B}_{ij}) \tag{18}$$

is a Z-number consisting of a triangular fuzzy number $\tilde{A}_{ij}$representing the relative preference of criterion $C_i$over C_j, and a triangular fuzzy number $\tilde{B}_{ij}$representing the reliability of this judgment [16].

The comparison matrix satisfies the following properties:

1. Reciprocity:

$$Z_{ij} = \frac{1}{Z_{ji}}, Z_{ii} = (1,1) \tag{19}$$

This ensures consistency in expert judgments.

2. Square structure: Z is an $n \times n$ square matrix, where n is the number of criteria.

Once the Z-number comparison matrix is constructed, the reliability components $\tilde{B}_{ij}$ are defuzzified using the centroid method:

$$\alpha_{ij} = \frac{l_{B_{ij}} + m_{B_{ij}} + u_{B_{ij}}}{3} \tag{20}$$

and the fuzzy restriction $\tilde{A}_{ij}$ is weighted by α_{ij} to obtain an equivalent triangular fuzzy number:

$$\tilde{A}_{ij}^{eq} = \alpha_{ij} \cdot \tilde{A}_{ij} = (\alpha_{ij} l_{A_{ij}}, \alpha_{ij} m_{A_{ij}}, \alpha_{ij} u_{A_{ij}}) \tag{21}$$

This transformation produces a fuzzy comparison matrix suitable for standard fuzzy AHP calculations, such as computing geometric mean weights, normalizing them, and ultimately ranking the alternatives or criteria.

3. Case Study Example: Evaluation of cutting-edge technologies

3.1. Case Study Design and Data Preparation

Assume a government agency aims to identify the most promising cutting-edge technologies sustainable energy technologies (A), resource-efficient economy technologies (B), and multi-sector emerging technologies (C) to stimulate national economic growth. The following criteria are considered to assess technologies : C_1 - technological practicality, C_2 - ecological effect, C_3 - level of innovation preparedness, C_4 - adaptability that represented by Z-numbers. To support this decision, a fuzzy AHP approach integrated with Z-numbers is applied to capture both expert evaluations and their confidence levels. Economic development largely depends on selecting suitable technological innovations that can boost productivity, create new industries, and enhance quality of life. This process typically includes defining objectives, identifying potential technologies, evaluating them, and making final choices. The Fuzzy AHP method combined with Z-numbers offers a flexible and reliable decision-making framework, particularly effective when addressing vague, uncertain, or subjective criteria. Using linguistic terms, various technology options such as renewable energy technologies, circular economic technologies, and cross-cutting emerging innovations can be assessed based on criteria like technical feasibility, environmental impact, innovation readiness, and flexibility, all within the Z-number framework. Renewable energy technologies play a crucial role in developing sustainable, resilient, and economically viable energy systems. They are increasingly prioritized in energy strategies because they support environmental and climate goals, generate economic and social benefits, strengthen energy security, and align with evolving policy frameworks. Circular economy technologies aim to reduce waste, maximize resource efficiency, and extend product lifecycles. Applying circular economy principles in technology evaluation promotes reuse, recycling, and remanufacturing, thus minimizing dependence on raw materials. Such technologies also lower pollution, energy use, and emissions while fostering sustainable and competitive technological development. Cross-cutting emerging innovations span multiple sectors and often enhance or enable other technologies. Incorporating these innovations into technology selection ensures greater adaptability, connectivity, and scalability. They improve operational efficiency through automation and data insights, reduce lifecycle costs and risks, advance sustainability and resilience goals, accelerate innovation, and provide strategic advantages. Selecting technologies that integrate such innovations helps establish a dynamic, future-oriented, and efficient technological ecosystem. Economic development is strongly influenced by the selection of appropriate technological innovations that enhance productivity, stimulate new industries, and improve quality of life. This process generally involves several key stages : establishing objectives, identifying possible technologies, evaluating alternatives, and making final selections. The primary challenge is to balance diverse factors such as environmental sustainability, societal acceptance, technological readiness, and regulatory alignment. The Fuzzy AHP approach combined with Z-numbers provides a comprehensive and flexible framework for decision-making, particularly suitable for situations involving vague, uncertain, or subjective criteria. Sustainable energy technologies (A) focus on producing and utilizing energy in ways that minimize environmental harm and reduce dependence on finite fossil fuels. These technologies include solar, wind, hydro, geothermal, and bioenergy systems. They promote cleaner energy production, improve energy security, and support climate change mitigation by lowering greenhouse gas emissions. The integration of smart grids, energy storage solutions, and digital monitoring systems further enhances efficiency and reliability. By encouraging the transition to renewable energy sources, these technologies not only address environmental challenges but also stimulate innovation, job creation, and long-term economic resilience. Resource-efficient economy technologies (B) are central to the concept of the circular economy, which emphasizes waste reduction, recycling, and sustainable resource management. These technologies help optimize material usage, extend product lifecycles, and minimize environmental footprints across production and consumption systems. Examples include recycling and remanufacturing technologies, eco-design, waste-to-energy systems, and advanced material recovery processes. By reducing reliance on raw materials and lowering energy consumption, resource-efficient technologies enable industries to operate more sustainably while maintaining competitiveness. They also contribute to lowering pollution and conserving natural resources, aligning economic development with ecological balance. Multi-sector emerging technologies (C) such as artificial intelligence, the Internet of Things, blockchain, advanced materials, and 3D printing transcend individual sectors and act as enablers of innovation across the economy. These technologies improve efficiency, connectivity, and data-driven decision-making, while fostering adaptability and resilience in complex systems. For example, artificial intelligence, the Internet of Things enhances manufacturing automation and predictive maintenance, blockchain ensures transparency in supply chains, and 3D printing supports customized, low-waste production. Their cross-cutting nature allows for the integration of digital intelligence into various domains, amplifying productivity, sustainability, and innovation capacity. When choosing innovative technologies, assigning appropriate weights or evaluation criteria allows decision-makers to prioritize alternatives according to the specific goals and needs of a project or organization. Typical factors considered in technology selection include technological practicality, ecological effect, level of innovation preparedness, and adaptability. Common criteria considered in technology innovation selection include technical feasibility, environmental impact, innovation readiness, and flexibility. Technological practicality (C_1) refers to the extent to which technology can be effectively implemented and operated within real-world conditions. It involves assessing whether the technology is technically sound, reliable, and compatible with existing systems or infrastructure. This criterion also considers the availability of technical expertise, maintenance requirements, scalability, and performance under different operational environments. Evaluating technological practicality ensures that chosen innovations are not only theoretically effective but also feasible, efficient, and sustainable in actual application. Ecological effects (C_2) assessment examine how technology impacts the natural environment throughout its life cycle from production and operation to disposal. It involves evaluating factors such as energy consumption, emissions, waste generation, resource use, and potential harm to ecosystems. Technologies with lower ecological footprints are generally preferred, as they contribute to sustainability goals by minimizing pollution, conserving natural resources, and supporting biodiversity. Assessing ecological effects helps ensure that technological innovation aligns with environmental protection and long-term ecological balance. Level of innovation preparedness (C_3) considers how ready technology is for practical implementation and large-scale adoption. It evaluates aspects such as the maturity of technology e.g., through Technology Readiness Levels, availability of supporting infrastructure, technical expertise, and institutional or policy support. This criterion also assesses the capacity of organizations or regions to adopt, adapt, and integrate innovation effectively. By measuring innovation preparedness, decision-makers can identify technologies that are not only promising but also realistically deployable within existing economic and operational contexts. Adaptability (C_4) assessment evaluates how easily a technology can adjust to changing conditions, requirements, or environments. It measures the flexibility of the technology to be scaled up or down, integrated with existing systems, or modified for different applications. In decision-making processes, particularly in multi-criteria decision analysis, the significance of each criterion for different alternatives is often expressed through linguistic terms such as strong, medium, low, or very strong. These qualitative scales are widely applied in fuzzy logic to handle imprecise and uncertain information effectively. The linguistic terms corresponding to the two components of a Z-number are represented as triangular fuzzy numbers, as illustrated below. Linguistic terms for the restriction (first) component of a Z-number are defined as follows: Very small sure- (0.1,0.2,0.3), Small sure- (0.2,0.3,0.4), Medium sure - (0.3,0.4,0.5), Strong sure - (0.4,0.5,0.6), Very strong sure – (0.5,0.6,0.7), Extremal sure – (0.6,0.7,0.8). Based on this, the following steps describe how to apply fuzzy AHP combined with Z-numbers for selecting innovative technologies [17].

3.2. The Mathematical Formulation of the Proposed Fuzzy AHP Model with Z-numbers

The mathematical formulation of the offered method must be presented in a more coherent and explicit manner to ensure clarity, consistency, and reproducibility. All symbols and variables should be defined before use and applied uniformly throughout the paper. Let the set of criteria be $C = \{C_1, C_2, \dots, C_n\}$and the set of technology alternatives be $A = \{A_1, A_2, \dots, A_m\}$. The pairwise comparison between criteria C_i and C_j is expressed by a Z-number

$$Z_{ij} = (\tilde{A}_{ij}, \tilde{B}_{ij})$$

where $\tilde{A}_{ij}$ represents the fuzzy restriction (evaluation value) and $\tilde{B}_{ij}$ denotes the fuzzy reliability (confidence level) of this evaluation. Both components are modeled as triangular fuzzy numbers:

$$\tilde{A}_{ij} = (l_{ij}, m_{ij}, u_{ij}), \tilde{B}_{ij} = (l'_{ij}, m'_{ij}, u'_{ij})$$

Before introducing any computation, it should be clearly stated that the model assumes experts are sufficiently knowledgeable, also unbiased, pairwise comparison matrices are reciprocal, i.e.,

$$Z_{ij} = \frac{1}{Z_{ji}}$$

and the criteria are relatively independent. These assumptions define the conditions under which the results remain valid.

To integrate Z-numbers into the fuzzy AHP framework, each Z-number must be transformed into an equivalent fuzzy number. First, the reliability component $\tilde{B}_{ij}$ is defuzzified using the centroid method:

$$\alpha_{ij} = \frac{l'_{ij} + m'_{ij} + u'_{ij}}{3}$$

Then, the equivalent fuzzy number $\tilde{a}_{ij}$ is obtained by weighing the restriction component:

$$\tilde{a}_{ij} = \alpha_{ij} \cdot \tilde{A}_{ij} = (\alpha_{ij} l_{ij}, \alpha_{ij} m_{ij}, \alpha_{ij} u_{ij}).$$

This transformation explicitly shows how expert reliability influences the final fuzzy comparison values.

After constructing the fuzzy pairwise comparison matrix

$$\tilde{A} = [\tilde{a}_{ij}]_{n\times n},$$

Fuzzy weights of criteria are calculated using the geometric mean method. For each criterion C_i,

$$\widetilde{w}_i = \left(\prod_{j=1}^{n} \tilde{a}_{ij}\right)^{1/n}$$

The normalized fuzzy weights are then given by:

$$\widetilde{W}_i = \frac{\widetilde{w}_i}{\sum_{k=1}^{n} \widetilde{w}_k}$$

Since decision-making ultimately requires crisp values, defuzzification must be clearly defined. Using the centroid method, the crisp weight of each criterion becomes:

$$W_i = \frac{l_i + m_i + u_i}{3}$$

where (l_i, m_i, u_i) are the lower, modal, and upper bounds of the triangular fuzzy weight $\widetilde{W}_i$. Presenting the computational procedure in this structured form clarifies every transformation step and prevents ambiguity. The overall algorithm of the method can be summarized as follows: define criteria and alternatives, construct Z-number-based pairwise comparison matrices, transform Z-numbers into fuzzy numbers, compute fuzzy weights, normalize them, defuzzify the results, check consistency, and finally rank the cutting-edge technologies. By embedding formulas directly into a logically explained essay-style presentation, the mathematical foundation of the paper becomes transparent and rigorous. This approach not only resolves notation inconsistencies and missing explanations but also ensures that the fuzzy AHP with Z-numbers framework can be easily understood, reproduced, and extended by future researchers.

3.3. Solution of Problem

In this section, the proposed fuzzy AHP approach integrated with Z-numbers is applied to solve the problem of evaluating and prioritizing cutting-edge technologies in terms of their contribution to economic growth. The aim is to obtain a reliable and systematic ranking of the selected technologies by incorporating both expert judgments and the associated level of confidence in those judgments. The solution process consists of steps that are represented below:

Step 1: Construct a decision matrix that reflects the importance of each criterion across the various alternatives. This matrix serves as the foundation for evaluating and comparing technological options by quantifying expert judgments and preferences. Each element in the matrix corresponds to a specific criterion–alternative relationship, expressed through Z-numbers to capture both uncertainty and reliability in the assessments. The decision matrix enables a structured analysis of how well each alternative meets the evaluation criteria, facilitating a more transparent and data-driven selection of innovative technologies. Table 1 presents the structure of this matrix formulated using Z-numbers.

Table 1. Decision Matrix with Z-numbers

	C_1	C_2	C_3	C_4
A	(3, 5, 7; 0.4, 0.5, 0.6)	(5, 7, 9; 0.3, 0.4, 0.5)	(3, 5, 7; 0.4, 0.5, 0.6)	(3, 5, 7; 0.4, 0.5, 0.6)
B	(5, 7, 9; 0.3, 0.4, 0.5)	(3, 5, 7; 0.5, 0.6, 0.7)	(3, 5, 7; 0.3, 0.4, 0.5)	(1, 3, 5; 0.5, 0.6, 0.7)
C	(5, 7, 9; 0.5, 0.6, 0.7)	(5, 7, 9; 0.5, 0.6, 0.7)	(3, 5, 7; 0.4, 0.5, 0.6)	(1, 3, 5; 0.5,0.6, 0.7)

Step 2: Create a pairwise comparison matrix using Z-numbers for each pair of criteria. Creating a pairwise comparison matrix using Z-numbers means systematically comparing every pair of decision criteria like technological practicality, ecological effect, Level of innovation preparedness adaptability to determine how much more important one is than the other while also expressing how certain or reliable that judgment is. Table 2 displays the structure of the decision matrix employed to compare the criteria and determine their relative weights.

Table 2. Comparative Decision Matrix of Criteria

	C_1	C_2	C_3	C_4
C_1	(1, 1, 1; 0.6, 0.7, 0.8)	(0.2,0.25,0.3; 0.5, 0.6, 0.7)	(1.5, 2, 2.5; 0.4, 0.5, 0.6)	(3, 4, 5; 0.5, 0.6, 0.7)
C_2	(3.5, 4, 4.5; 0.5, 0.6, 0.7)	(1, 1, 1; 0.6, 0.7, 0.8)	(4.5, 5, 5.5; 0.7, 0.8, 0.9)	(3, 4, 5; 0.4, 0.5, 0.6)
C_3	(0.3,0.5,0.7; 0.4, 0.5, 0.6)	(0.18,0.2,0.22; 0.7, 0.8, 0.9)	(1, 1, 1; 0.6, 0.7, 0.8)	(0.2,0.25,0.3; 0.5, 0.6, 0.7)
C_4	(0.2,0.25,0.3; 0.5, 0.6, 0.7)	(0.2,0.25,0.3; 0.4, 0.5, 0.6)	(3, 4, 5; 0.5, 0.6, 0.7)	(1, 1, 1; 0.6, 0.7, 0.8)

Step 3. When dealing with eigenvalues and eigenvectors in the context of Z-numbers, the matrices are composed of Z-number elements rather than conventional real or complex numbers. To compute the eigenvalues of these Z-matrices, a modified characteristic equation incorporating Z-numbers must be solved. This process involves redefining determinants and characteristic polynomials to align with the Z-number framework. Typically, specialized algorithms developed for fuzzy systems where mathematical operations on Z-numbers are explicitly defined are applied to determine both the eigenvalues and the associated eigenvectors. Once the eigenvalues are obtained, the corresponding eigenvectors are derived by solving the respective equation $Zv = \lambda v$ for each eigenvalue λ, where Z is the comparison matrix, λ is the scalar eigenvalue, and v is the associated eigenvector [18]. The weights of the criteria are subsequently determined through this procedure. Weight of criteria C_1 is (0.1756, 0.1759, 0.176; 0.28, 0.308, 0.3309), weight of criteria C_2 is (0.542, 0.5425, 0.543; 0.28, 0.281, 0.283), weight of criteria C_3 is (0.0884, 0.0886, 0.0888; 0.28, 0.281, 0.283), weight of criteria C_4 is (0.1931, 0.1933,0.1935; 0.2801, 0.2804, 0.2805).

Step 4: Normalizing the weighted decision matrix, as shown in Table 3, involves rescaling the values so they are expressed on a consistent scale. When evaluating alternatives, each criterion may be measured in different units or scales e.g., dollars, percentages, scores. Normalization converts all these values into a common scale, usually between 0 and 1, so that no single criterion dominates the decision due to its numerical range. After normalization, the matrix is called the normalized decision matrix. Then, by multiplying each normalized value by its corresponding criterion weight, determined the weighted normalized decision matrix, which reflects both the performance of alternatives and the relative importance of each criterion. Normalizing the weighted decision matrix ensures that all criteria are evaluated on a fair, consistent basis and allows for accurate comparison among alternatives.

Table 3. Weighted Decision Matrix with Z-numbers

	C_1	C_2	C_3	C_4
A	(0.001,0.16,0.40; 0.4, 0.5, 0.6)	(0.24, 0.46, 0.67; 0.3, 0.4, 0.5)	(0.001, 0.18 0.39; 0.4, 0.5, 0.6)	(0.25, 0.46, 0.68; 0.4, 0.5, 0.6)
B	(0.24,0.56,0.67; 0.3, 0.4, 0.5)	(0.001,0.17,0.40;0.5, 0.6, 0.7)	(0.001,0.18, 0.39, 0.3, 0.4, 0.5)	(0.001, 0.2, 0.42; 0.5, 0.6, 0.7)
C	(0.24, 0.46, 0.67; 0.5, 0.6, 0.7)	(0.24, 0.46, 0.67; 0.5, 0.6, 0.7)	(0.001,0.18, 0.39; 0.4, 0.5, 0.6)	(0.001,0.21,0.42; 0.5, 0.6, 0.7)

Step 5. Ranking alternatives. It means ordering all the possible options (alternatives) from best to worst based on their overall performance scores. After computing the weighted normalized decision matrix, each alternative has an aggregate score that reflects how well it satisfies all evaluation criteria.

These scores are then compared to the higher (or lower, depending on the context) the score, the better the alternative. Finally, the alternatives are ranked accordingly to help decision-makers identify the most suitable or optimal choice. Ranking alternatives is the process of determining which option performs best overall, helping decision-makers choose the most effective and reliable solution. For ranking the alternatives, the Hellinger distance is calculated for each option. Distance between option A and Z (1) is 2.23, distance between option B and Z (1) is 1.65, distance between option C and Z (1) is 2.45. Results for alternatives: A= 2.23, B = 1.65, C = 2.45. Comparison of options represents that alternative B - resource-efficient economic technologies is best option.

4. Conclusion

Achieving sustainable economic growth increasingly depends on the careful selection and implementation of technological innovations. However, this process has become more challenging due to rising uncertainties driven by volatile markets, environmental issues, changing regulations, and rapid technological advancements. In such an unpredictable context, decision-makers must evaluate not only the long-term economic and environmental benefits of new technologies but also manage the inherent risks associated with their adoption. Conventional evaluation methods often prove inadequate in these situations, creating a demand for more adaptable, resilient, and forward-looking decision-making frameworks. These frameworks need to balance environmental sustainability, economic viability, and technical feasibility while anticipating uncertain future developments. As a result, aligning innovation strategies with sustainability goals has become a priority across government, industry, and academia. This study explores how technology selection processes are evolving to meet these uncertainties and emphasizes strategic approaches that can support sustainable economic development. By examining current practices, innovation patterns, and practical applications, it aims to identify effective models that foster both innovation and sustainability amid uncertainty. Selecting suitable technological innovations is crucial for promoting sustainable economic growth, especially in environments characterized by uncertainty and incomplete information. This research demonstrates that integrating advanced decision-making tools such as fuzzy AHP combined with Z-numbers offers a robust framework that addresses both the ambiguity in expert judgments and the reliability of data. Effectively managing uncertainty with this method enhances the accuracy and trustworthiness of technology selection decisions. Evaluation of renewable energy, circular economy, and emerging technologies against key sustainability criteria highlight the strong potential of circular economy technologies to support long-term sustainable development. Overall, the approach presented provides a flexible and practical tool for policymakers and organizations aiming to make informed and resilient decisions aligned with sustainable economic objectives under uncertain conditions. Future research can further refine these models to keep pace with evolving technologies and market shifts, ensuring their relevance in dynamic environments. The fuzzy multi-attribute decision-making approach using Z-numbers is applied to assess three technological options - sustainable energy technologies, resource-efficient economy technologies, and multi-sector emerging technologies based on criteria such as technological practicality, ecological effect, level of innovation preparedness, and adaptability. Incorporating Z-numbers into this framework enhances the innovation selection process by effectively handling uncertainty and grounding decisions in reliable information. The comparison of options suggests that, under the given conditions, resource-efficient economic technologies are the optimal choice for sustainable economic growth. This research shows that the fuzzy AHP method offers a structured and adaptable framework for assessing advanced technologies according to their potential impact on economic growth in uncertain conditions. By integrating fuzzy logic with linguistic evaluations, the model more accurately reflects human reasoning compared to conventional crisp approaches and allows for a systematic analysis of complex and multidimensional technological criteria. The findings emphasize the usefulness of fuzzy AHP as a decision-support instrument for policymakers, investors, and strategic decision-makers who need to rank emerging technologies in uncertain economic settings.

Nevertheless, the proposed framework has certain limitations. Its primary shortcoming is its heavy reliance on expert opinions, which are inherently subjective and may be shaped by individual experience, institutional bias, or limited information. Differences in expert selection, panel composition, or aggregation methods can produce variations in the final rankings. Furthermore, the outcomes are sensitive to the specification of membership functions, linguistic variables, and weighting procedures, which may influence the consistency and reliability of the results. As the number of criteria and alternatives grows, the pairwise comparison process also becomes more demanding and complex, potentially reducing evaluation consistency. The performance of the model is also dependent on several key assumptions. It presumes that the experts involved have comprehensive and balanced expertise in both technological innovation and economic development, and that the chosen criteria effectively represent the main determinants of economic growth. Additionally, the framework assumes a relatively stable decision-making environment and a sufficient level of independence among the evaluation criteria. If these conditions are not met, the credibility of the results may be weakened. Furthermore, the approach may be less suitable for highly dynamic and fast-changing technological environments, where the economic significance of innovations can shift rapidly. In such situations, regular revisions of expert assessments and criteria weights would be necessary to maintain the model's relevance. Likewise, when strong interdependencies exist among evaluation criteria, fuzzy AHP alone may be insufficient to capture the underlying causal structure, and hybrid or network-based methods could offer a more comprehensive and accurate analysis.

Future research should therefore focus on enhancing the robustness and applicability of the model. Integrating fuzzy AHP with methods such as DEMATEL, ANP, or TOPSIS could help account for interrelationships among criteria and improve decision accuracy. Sensitivity and scenario analyses would further strengthen the reliability of the results by identifying critical parameters that most influence rankings. In addition, validating the framework with real economic performance indicators and applying it across different countries, sectors, and technological domains would improve its generalizability.

Overall, while the fuzzy AHP framework presents a powerful and practical tool for evaluating cutting-edge technologies under uncertainty, its results should be interpreted with careful consideration of its assumptions and limitations. Acknowledging these factors not only enhances the scientific rigor of the study but also provides a clearer foundation for future methodological improvements and real-world applications.

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