IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 12 July 2023, accepted 25 July 2023, date of publication 28 July 2023, date of current version 7 August 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3299861

RESEARCH ARTICLE

Optimizing New Technology Implementation Through Fuzzy Hypersoft Set: A Framework Incorporating Entropy, Similarity Measure, and TOPSIS Techniques

MUHAMMAD AHSAN[1,2], MUHAMMAD AMAD SARWAR[3], SHOWKAT AHMAD LONE[4], SALMEH A. ALMUTLAK[4], AND SADIA ANWER[5]

[1]Department of Mathematics, Riphah International University, Faisalabad 37450, Pakistan
[2]Department of Mathematics, University of Management and Technology, Lahore 54770, Pakistan
[3]School of Mathematics, Nanjing University of Aeronautics and Astronautics, Nanjing 211106, China
[4]Department of Basic Sciences, Saudi Electronic University, Riyadh 11673, Saudi Arabia
[5]Department of Mathematics, Prince Sattam bin Abdulaziz University, Al-Kharj 11991, Saudi Arabia

Corresponding author: Muhammad Ahsan (ahsan1826@gmail.com)

ABSTRACT As each day passes by the world's NT requirements increase due to increasing population and technological advancements. Currently, traditional technologies are inadequate to support the requirement. It is vital to investigate cost-effective and suitable green environmental technologies as a response. Future connectivity(5G, 6G), programming, artificial intelligence and new technologies might be a resolution to this resource crisis in this setting. Now, choosing amongst the most suitable option present itself as a Multi-Criteria Decision Making (MCDM) challenge in which a judgment must be made in terms of a wide variety of characteristics. In this paper, the extended MCDM strategies are proposed to optimizing new technologies implementation. The novelty of the Fuzzy Hypersoft (FHS) set is discussed, which can deal with uncertainties, vagueness, and unclear data. This framework is more flexible than the structures found in literature as it can deal with the information where the attributes can be further sub-partitioned into attribute values for a better understanding. It may not always be possible to analyze these criteria using precise figures; instead, an assessment must be made using human and expert judgments for a more adaptable and sensitive review. The adaptive MCDM design with fuzzy edges incorporates Entropy (EN), Similarity Measure (SIM), and TOPSIS techniques rely on FHS. The conveyed frameworks are better for probing NT issues because they analyze a more expansive range of attributes, which can handle a component with multiple different sub-attribute values. Expert ratings are used to demonstrate a practical application to highlight the relevance of the proposed approach. In addition, a sensitivity analysis is done to investigate the impact of primary criterion weights in sorting.

INDEX TERMS New technologies (NT), risk factors (RF), planning and development, multi-criteria decision making (MCDM), entropy (EN), similarity measures (SIM), fuzzy hypersoft set (FHS).

I. INTRODUCTION

Implementing new technologies in organizations presents both opportunities and risks. To ensure a smooth transition and maximize the benefits, it is essential to prioritize and address potential risk factors. Identifying and managing these risks early on significantly improves the likelihood of a successful and effective implementation. The prioritization of risk factors plays a crucial role in this context. It involves evaluating and ranking potential risks based on their potential impact and likelihood of occurrence. By focusing on the most critical risk factors, organizations can allocate resources efficiently, develop appropriate mitigation strategies, and minimize the negative consequences associated with technology

The associate editor coordinating the review of this manuscript and approving it for publication was Alba Amato.

implementation. Effectively prioritizing risk factors requires a comprehensive understanding of the organization's goals, objectives, and specific context [13].

It involves considering various aspects, such as technical challenges, organizational readiness, stakeholder engagement, and potential disruptions to existing processes. Additionally, recognizing that the significance of risk factors may vary across industries highlights the need for a tailored approach. Organizations can employ different frameworks and methodologies to prioritize risk factors. These include risk assessment matrices, risk scoring techniques, or qualitative assessments based on expert judgment. By utilizing these approaches, organizations can systematically evaluate and rank risks, enabling decision-makers to allocate resources, establish appropriate risk management strategies, and make informed choices throughout the implementation process.

The ineptitude of parametrization initiatives could precipitate these side effects [17]. Molodtsov [40] indicated the soft set (SS) supposition as a computational intelligence strategy for interacting with unpredictability or uncertainty that does not apply to the previously stated troubles. SS pertains to primitive systems in close proximity [41] and is an excellent explanation of attempting to set deferential FS, as mentioned by Thielle [42]. By merging SS and FS, Maji et al. [43] developed the concept of the fuzzy soft set (FSS). Maji et al. [44] pioneered the use of FSS theory in object recognition misgivings. Maji et al. [43] conceptualized FSS by merging SS and FS. Yang et al. [45] proposed an FSS principle by blending the FS and SS and incorporating it in the decision-making problems. The fuzzy event's possibility indexes have significantly contributed to FS and their premixed paradigms discussed in [46]. De Luca and Termini [47] proposed a specific configuration of suppositions for fuzzy EN. On the other hand, EN has received increasing attention than SIM, a powerful skill for estimating the concentration of SIM between two factors. The EN and SIM for diverse sorts, such as interval-valued fuzzy set (IVFS) [48], FSS [53], and intuitionistic fuzzy soft set (IFSS) [50], have been comprehensively used in resolving decision making, sensory perception, and spectrum sensing concerns.

The decomposition of influential factors and generalized divergence-based decision making method can be achieved through brainstorming or checklist techniques. These factors can then be evaluated using fuzzy reasoning membership functions and prioritized using the analytic hierarchy process (AHP) [1], [3], [5], [79]. AHP is a widely recognized decision-making technique for prioritizing alternatives based on multiple criteria and attributes. The use of AHP does not necessarily require complex mathematics but involves decomposing the problem, making pair-wise comparisons, and creating priority vectors. However, the current AHP method has a limitation in dealing with uncertain scales in real-world construction problems, which are often complex and involve significant uncertainties and subjective judgments. To address this limitation, a modified AHP method is proposed to enhance its applicability in construction risk analysis.

A comprehensive risk analysis should encompass all aspects of risks involved in the construction process and outline measures to minimize these risks. It should provide sufficient details to identify and evaluate hazards that could potentially lead to project failure, along with demonstrating the implementation of appropriate measures to reduce risks to As Low As Reasonably Practicable (ALARP) [1], [4]. A typical risk assessment framework consists of four stages: risk identification, risk assessment, risk response, and risk monitoring and review [6], [7]. However, the nature of construction introduces considerable uncertainties and subjectivities, which pose challenges to the applicability of many commonly used risk assessment methods in the construction industry. Fuzzy reasoning techniques have proven valuable in addressing ambiguous and complex problems encountered in construction projects, enabling reliable decision-making [8].

For ease of understanding, the attributes are separated into sub-amounts in different adoption and implementation ranges. Smarandache [54] met this criterion by improving the FHS set (FHSS) as an outgrowth of the SS. He enlarged this standpoint by re-envisioning SS as a multi-attribute framework and concluding it to the FHSS. Saeed et al. [49], [55], [72] presented some concepts such as Hypersoft (HS) and used SIM methodologies for a medical situation in a neutrosophic atmosphere. Saeed et al. [55], [63], [63], [71], [72], [73], [74], [75], [76], [77] several implementations of SS, intuitionistic set, and intuitionistic HSS in machine vision, biomaterials, discernment, and defined mapping in an HSS concept. Abbas et al. [70] looked at hypersoft points in a wide assortment of distorted contexts. Please see Table 1 for clear comprehension.

A. MOTIVATIONS

As it is complicated to discern specialized data of NT approaches employed prior around the globe, existing understanding and data treatments [39], [40], [43], [51], and [52] are restricted to obtain configuration settings, the purpose of this study is to forecast plausible contexts for NT schemes, as well as their effectual recognizing treatment. The strategies described in [39], [40], [43], [51], [52], and [78] are unsatisfactory for a meticulous analysis of the data to have a better insight and make sound decisions. These assumptions fail to maintain when the characteristics have sub-parameters with different types of individuals, as shown in [39], [40], [43], [51], [52], and [78]. The extended MCDM strategies are based on evaluating NT choices in Turkey. To accomplish this goal, these methodologies are consolidated into an FHSS comprised entirely by merging FS and HSS. The adaptive fuzzy MCDM model incorporates EN, SIM, and TOPSIS techniques that rely on FHSS.

B. CONTRIBUTIONS

The presented structures are suitable options for exploring NT involved because it facilitates a broader spectrum of

TABLE 1. Research gap, advantages and disadvantages.

Theories/nature	Year	M.	P.	SP.	PN.
Fuzzy set (Zadeh et al.)	1965	✓	×	×	×
Soft set (Molodtsov et al.)	1999	✓	✓	×	×
Fuzzy soft set (Maji et al.)	2001	✓	✓	×	×
Intuitionistic fuzzy set (Atanassov et al.)	1983	✓	×	×	×
Neutrosophic set (Smarandache et al.)	1998	✓	×	×	×
Complex fuzzy set (Ramotet et al.)	2002	✓	×	×	✓
Proposed method	2022	✓	✓	✓	✓

Legend: Membership=M, Parameters=P,
Sub parameters=SP, Periodic nature=PN

membership grades, which can deal with situations where an attribute has numerous sub-attributed values. Experts ratings are used to demonstrate the useful applications and highlight the proposed approach's relevance. In addition, a sensitivity analysis is done to investigate the impact of primary criterion weights in sorting. The recommendations involved NT approaches primarily on Accessibility, Technical characteristics, Environmental factors, Technological stability, Installation and performance, Factors influencing the economy, Political and Social influences variables. When applied in combination with scientific modeling, these assumptions are essential for accomplishing any plausible option.

C. THE DEMONSTRATION OF THE PAPER

Section *II* focuses on some of the paper's fundamental precepts and terminologies. In Section *III*, *IV*, a proverbial relevance of EN and SIM for FHSS, respectively, is supported by examples. In Section *V*, TOPSIS is used to demonstrate a practical application to highlight the relevance of the proposed approach. In addition, a sensitivity analysis is done to investigate the impact of primary criterion weights in sorting. Section *VI* concludes the paper, please see Fig 1 for frame diagram to clarify the working of the algorithms.

II. PRELIMINARIES

Numerous origins are described in this section of the article, along with FS, SS, EN, SIM, and FHSS.

Definition 1: The FS, $R = \{(c, \vartheta(c))|\ c \in K\}$ in such a way

$$\vartheta : K \to [0, 1],$$

where K personifies collection of objects and $\vartheta(c)$ exemplifies the membership level of $c \in K$. FS have been developed by Zadeh [39].

Definition 2: SS is the pair (ϑ, J) over K, where ϑ is a mechanism that looks something like this:

$$\vartheta : J \to P(K),$$

for $o \in J$, $\vartheta(o)$ can be anticipated as o mathematical abstractions of the SS aspects (ϑ, J). This theory have been presented by Molodtsov [40].

Definition 3: An EN is a factual map ϕ from $FS(\vartheta, J)$ to $[0, \infty)$ for FSS if ϕ fulfill the minimum necessities,

1) $\phi(\vartheta, J) = 0$ if (ϑ, J) is a SS,
2) $\phi(\vartheta, J) = 1$ if $\vartheta(w) = 0.5$, for $w \in J$, where $[0.5]$ is the FS is the level of membership function $[0.5](b) = 0.5$, for every $b \in K$,
3) Suppose (ϑ, J) be crisper as compare to (ψ, K) which is, for $w \in J$ and $b \in K$, $\vartheta(w)(b) \leq \psi(w)(b)$ if $\psi(w)(b) \leq 0.5$ and $\vartheta(w)(b) \geq \psi(w)(b)$ if $\psi(w)(b) \geq 0.5$. Then $\phi(\vartheta, J) \leq \phi(\psi, K)$,
4) $\phi(\vartheta, J) = \phi(\vartheta^c, J)$, where (ϑ^c, J) is the complement of FSS (ϑ, J), which can be displayed as $\vartheta^c(w) = (\vartheta(w))^c$, for every $w \in J$. Liu et al. [53] developed the EN which is popular weighting approach to evaluating value disparity in selection.

Definition 4: A map W from $FS(K, R)\times FS(K, R)$ to $[0, 1]$ fulfils the quality requirements, it is labelled as an SIM for FSS.

1) $W(X_K, \Phi_K) = 0$, for any $K \in R$, and $W((\vartheta, J), (\vartheta, J)) = 1$ for any $(\vartheta, J) \in FS(K, R)$,
2) $W((\vartheta, J), (\psi, K)) = W((\psi, K), (\vartheta, J))$, for any $(\vartheta, J), (\psi, K) \in FS(K, R)$,
3) For any $(\vartheta, J), (\psi, K), (K, L) \in FS(K, R)$ if $(\vartheta, J) \subseteq (\psi, K) \subseteq (K, L)$, then $W((K, L), (\vartheta, J)) = min(W((K, L), (\psi, K)), W((\psi, K), (\vartheta, J)))$. Liu et al. [53] developed the SIM which means that how closely connected or identical datasets are to one another.

Definition 5: Suppose that K and $\vartheta(K)$ are the acquisition as well as all ambiguous subsets of K respectively, let $t_1, t_2, t_3, \cdots, t_n$ be determining factors with character traits that match up to the sets $G_1, G_2, G_3, \ldots, G_n$, respectively. where $G_i \cap G_j = \Phi$ for $i \neq j$ and i, j refers to $\{1, 2, 3, \ldots, n\}$. The FHSS is the pair (Σ_L, L) over K categorised by a map $\Sigma_L : L \to \vartheta(K)$, where $L = G_1 \times G_2 \times G_3 \times \ldots \times G_n$. Smarandache [54] met this criterion by improving the FHSS as an outgrowth of the SS.

III. THE EN-BASED FHSS OFFERED WITH IMPLEMENTATION

EN is amongst the most pertinent characteristics of FS because it manages critical FS regulatory frameworks.How can one calculate the degree of uncertainty in an FS? EN is a method for estimating FS uncertainties. This section augmented the construct of EN within the context of FHSS. Specific respective theoretical constructs and integration are addressed to illustrate the reliability and applicability of the construction of new EN-based FHSS.

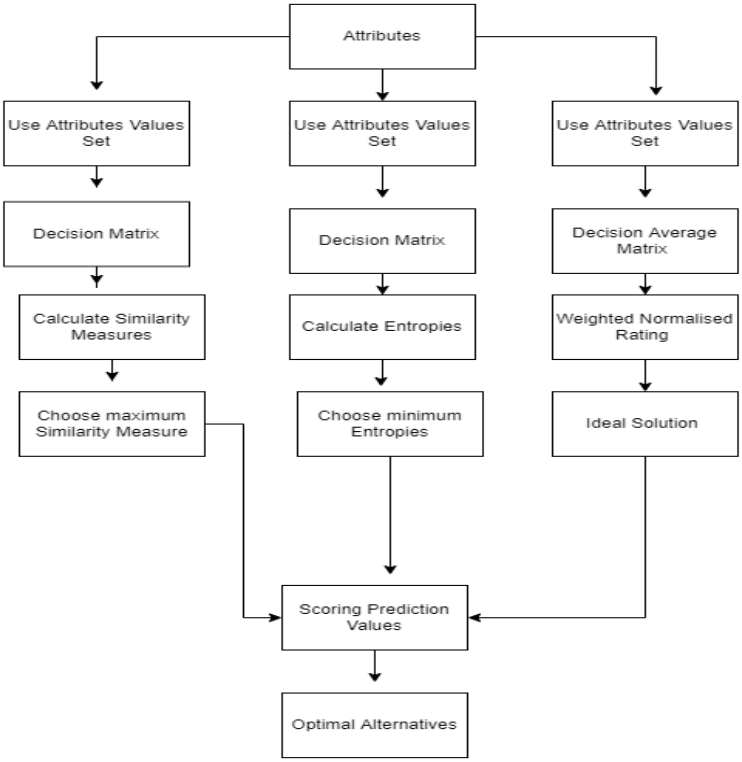

FIGURE 1. Frame diagram for proposed algorithms.

Definition 6: A real function $E : FHS(\mathcal{U}) \to R^+ \cup \{0\}$ is named an entropy on FHS set, if E satisfies all the following properties,

1) $E(\xi) = 0$ iff $\xi \in FHS(\mathcal{U})$.
2) $E(\xi) = mn$ iff $u_{\Psi(g)}(x) = 0, \forall g \in E$ and $\forall x \in \mathcal{U}$.
3) $E(\xi) = E(\xi^c)$ for all $\xi \in FHS(\mathcal{U})$.
4) $E(\xi) \leq E(\zeta)$ if $\zeta \subseteq \xi$, where $\xi = (\Psi_1, G_1)$, and $\zeta = (\Psi_2, G_2)$.

A. PROPOSITION

Let $\xi = (\Psi_1, G_1)$ be a FHS set, $E : FHS(\mathcal{U}) \to R^+ \cup 0$ be a mapping. Then $E(\xi) = \sum_{j=1}^{n} \sum_{i=1}^{m} (1 - (u_{\Psi_1(g_j)}(x_i))$ is a FHS entropy for $\xi = (\Psi_1, G_1)$.

B. ALGORITHM

Suppose X be the universal set and let $G = Q_1 \times Q_2 \times \ldots \times Q_n$, where $n \geq 1$ and Qi is the compendium of all valuable features. The methodologies for the envisaged FHSS-based EN are as described in the following.

1) Input each of the FHSS.
2) By using Proposition (A), determine the EN for each FHSS.
3) Consider a FHSS with the smallest amount of EN and choose it for the best conceivable result.
4) would choose anyone if it procured more than one.

C. EXAMPLE

As each day passes by, the world's NT requirements increase due to increasing population and technological advancements. Currently, traditional technologies are inadequate to support the requirement. It is vital to investigate cost-effective and suitable technologies as a response. 3D-printing, future connectivity(5G, 6G), programming, quantum computing, and artificial intelligence might be a resolution to this resource crisis in this setting. But new technologies implementation faces various risk factors. There are four $X = \{a =$ 3D Printing $b =$ 6G internet $c =$ Quantum computing $\}$ new technologies implementation faces various risk factors understudy, let $a_1 =$ Security Risk, $b_2 =$Integration Risk, $c_3 =$Operational Risk, $d_4 =$Financial Risk $e_5 =$Regulatory Risk be unique features with respective attribute values which belong to gatherings Q_1, Q_2, Q_3. He wishes to pick the optimum NT choices. Let $Q_1 = \{\eta_1 =$ Durability, $\eta_2 =$ Sustainability$\}$, $Q_2 = \{\eta_3 =$ Insufficient communication$\}$, $Q_3 = \{\eta_4 =$ Affordability, $\eta_5 =$ Contribution to economy$\}$, where $Q_1 \times Q_2 \times Q_3 = G_1 = \{g_1, g_2, g_3, g_4\}$.

1) The management can incorporate this evidence in the form of FHSS with the guidance of decision makers $(\psi, \mathcal{F})$, $(\varphi, \mathcal{F})$ and $(\chi, \mathcal{F})$ respectively, 3D Printing $= \xi = (\psi, \mathcal{F}) = \{\Psi_1(g_1) = \{\langle u_1, 0.3\rangle, \langle u_2, 0.5\rangle, \langle u_3, 0.2\rangle\}$, $\Psi_1(g_2) = \{\langle u_1, 0.2\rangle, \langle u_2, 0.8\rangle, \langle u_3, 0.1\rangle\}$, $\Psi_1(g_3) = \{\langle u_1, 0.7\rangle, \langle u_2, 0.8\rangle, \langle u_3, 0.4\rangle\}$, $\Psi_1(g_4) = \{\langle u_1, 0.4\rangle, \langle u_2, 0.6\rangle, \langle u_3, 0.8\rangle\}\}$, 6G internet$= \zeta = (\varphi, \mathcal{F}) = \{\Psi_1(g_1) = \{\langle u_1, 0.4\rangle, \langle u_2, 0.3\rangle, \langle u_3, 0.5\rangle\}$, $\Psi_1(g_2) = \{\langle u_1, 0.1\rangle, \langle u_2, 0.9\rangle, \langle u_3, 0.4\rangle\}$, $\Psi_1(g_3) = \{\langle u_1, 0.5\rangle, \langle u_2, 0.2\rangle, \langle u_3, 0.3\rangle\}$, $\Psi_1(g_4) = \{\langle u_1, 0.6\rangle, \langle u_2, 0.2\rangle, \langle u_3, 0.6\rangle\}\}$, Quantum Computing$= \eta = (\chi, \mathcal{F}) = \{\Psi_1(g_1) =$

$\{\langle u_1, 0.4\rangle, \langle u_2, 0.9\rangle, \langle u_3, 0.1\rangle\}$, $\Psi_1(g_2) = \{\langle u_1, 0.2\rangle, \langle u_2, 0.4\rangle, \langle u_3, 0.5\rangle\}$, $\Psi_1(g_3) = \{\langle u_1, 0.4\rangle, \langle u_2, 0.5\rangle, \langle u_3, 0.2\rangle\}$, $\Psi_1(g_4) = \{\langle u_1, 0.6\rangle, \langle u_2, 0.2\rangle, \langle u_3, 0.5\rangle\}\}$,

2) The entropies can be calculated by using Proposition (A) $E(\xi) = 6.2$, $E(\zeta) = 6$, $E(\eta) = 7.1$,
3) The ideal solution is to use $(\varphi, \mathcal{F})$ because it has the lowest number of EN.
4) 6G is the best NT.

D. COMPARATIVE STUDIES

Several examinations of the previous techniques with shortcomings are explored to measure the proposed technique's reliability and supremacy. All existing restraints are abolished when the aspects are further separated into data points. The predicted EN-depend will address this prerequisite on FHSS. For more detail, please see Table 2.

IV. SELECTION OF NT RESOURCES BASED ON SIMILARITY MEASURE OF FHS SET

Here, distance Measures (DM) are discussed between FHS sets and propose a proverbial definition of SIM for FHS sets.

Definition 7: Suppose that $\xi = (\Psi_1, G_1)$, $\zeta = (\Psi_2, G_2)$ and $\eta = (\Psi_3, G_3)$ are three FHS sets in universe $\mathcal{U}$. Assume d is a mapping, $d : FHS(\mathcal{U}) \times FHS(\mathcal{U}) \rightarrow R^+ \cup \{0\}$ and it possesses the following features:

- $d(\xi, \zeta) \geq 0$,
- $d(\xi, \zeta) = d(\zeta, \xi)$,
- $d(\xi, \zeta) = 0$ iff $\xi = \zeta$,
- $d(\xi, \zeta) + d(\zeta, \eta) \geq d(\xi, \eta)$.

Then $d(\xi, \zeta)$ is called a DM between FHS sets ξ and ζ.

Definition 8: A real function $S : FHS(\mathcal{U}) \times FHS(\mathcal{U}) \rightarrow [0, 1]$ is called a SIM between two FHS, $(\Psi_1, G_1) = [a_{ij}]_{m\times n}$ and $(\Psi_2, G_2) = [b_{ij}]_{m\times n}$ if S meets the required conditions,

1) $S(\xi, \zeta) \in [0, 1]$.
2) $S(\xi, \zeta) = 1$ iff $[a_{ij}]_{m\times n} = [b_{ij}]_{m\times n}$.
3) $S(\xi, \zeta) = S(\zeta, \xi)$.
4) $S(\xi, \eta) \leq S(\xi, \zeta)$ and $S(\xi, \eta) \leq S(\zeta, \eta)$ if $\xi \subseteq \zeta \subseteq \eta$ for any $\eta \in FHS(\mathcal{U})$.

Definition 9: Let $\mathcal{U} = \{x_1, x_2, \ldots, x_m\}$ be an initial universe development. Suppose that $\xi = (\Psi_1, G_1)$ and $\zeta = (\Psi_2, G_2)$, are two FHS sets, $\Psi_1(g) = \{x, \mu_{\Psi_1(g)}(x), g \in G, x \in \mathcal{U}\}$, $\Psi_2(g) = \{x, \mu_{\Psi_2(g)}(x), g \in G, x \in \mathcal{U}\}$, The appropriate distances are then determined for ξ and ζ.

1) The Hamming distance, $d^H_{FHS}(\xi, \zeta) = \sum_{j=1}^{n}\sum_{i=1}^{m} |\Delta_{ij}u(x)|$, where $\Delta_{ij}u(x) = u_{\Psi_1(g_j)}(x_i) - u_{\Psi_2(g_j)}(x_i)$,
2) The normalized Hamming distance, $d^{nH}_{FHS}(\xi, \zeta) = \frac{d^H_{FHS}(\xi,\zeta)}{mn}$
3) The Euclidean distance, $d^E_{FHS}(\xi, \zeta) = \left(\sum_{j=1}^{n}\sum_{i=1}^{m} \frac{|\Delta_{ij}u(x)|^2}{3}\right)^{\frac{1}{2}}$, where $\Delta_{ij}u(x) = u_{\Psi_1(g_j)}(x_i) - u_{\Psi_2(g_j)}(x_i)$,
4) The normalized Euclidean distance, $d^{nE}_{FHS}(\xi, \zeta) = \frac{d^H_{FHS}(\xi,\zeta)}{\sqrt{mn}}$

Here, it is clear that the following properties holds,

1) $0 \leq d^H_{FHS}(\xi, \zeta) \leq mn$ and $0 \leq d^{nH}_{FHS}(\xi, \zeta) \leq 1$
2) $0 \leq d^E_{FHS}(\xi, \zeta) \leq \sqrt{mn}$ and $0 \leq d^{nE}_{FHS}(\xi, \zeta) \leq 1$

It is notable that SIM can be produced from DM. Hence, we may utilize the proposed DM to characterize SIM between Fuzzy hypersoft sets. In view of the relationship of SIM and DM, a few SIM between FHS sets $\xi = (\Psi_1, G_1)$ and $\zeta = (\Psi_2, G_2)$ are characterized as follows;

$$S^H_{FHS}(\xi, \zeta) = \frac{1}{1 + d^H_{FHS}(\xi, \zeta)}$$
$$S^E_{FHS}(\xi, \zeta) = \frac{1}{1 + d^E_{FHS}(\xi, \zeta)}$$
$$S^{nH}_{FHS}(\xi, \zeta) = \frac{1}{1 + d^{nH}_{FHS}(\xi, \zeta)}$$

and

$$S^{nE}_{FHS}(\xi, \zeta) = \frac{1}{1 + d^{nE}_{FHS}(\xi, \zeta)}$$

A. ALGORITHM

Suppose X be the universal set and let $G = Q_1 \times Q_2 \times \ldots \times Q_n$, where $n \geq 1$ and Qi is the compendium of all valuable features. The methodologies for the envisaged FHSS-type SIM are as described in the following.

1) Insert each of the FHSS.
2) Establish the SIM for each FHSS using definition 8.
3) Choose the FHSS with the most similarities.
4) Choose one of the optimums if it earned more than one.

B. EXAMPLE

Emerging technologies such as Artificial Intelligence (AI), Software 2.0, Programming, and Robotics are transforming diverse industries and sectors. AI entails replicating human intelligence in machines, enabling them to carry out activities like decision-making and problem-solving. Software 2.0 signifies a transition towards utilizing machine learning and AI methods to construct software that can acquire knowledge from data. Programming refers to the procedure of developing computer programs using programming languages. Robotics encompasses the creation and utilization of robots that possess the ability to perform tasks in the physical realm. These advancements hold the promise of revolutionizing fields such as automation, healthcare, and more. It is essential in developing countries to obtain the proper continuous supply that has a low impact on the environment, budget, and business. This endeavor benefits a handful of individuals. Availability, stability, and productivity are essential to address while evaluating viable NT resources. From Example C,

1) Our purpose is to explore the perfect NT source based on established of standards. The FHSS concept is included in this setting below.
Artificial Intelligence $\xi = (\varphi, \mathcal{F}) = \Psi_1(g_1) = \{\langle u_1, 0.3\rangle, \langle u_2, 0.5\rangle, \langle u_3, 0.2\rangle\}$, $\Psi_1(g_2) = \{\langle u_1, 0.2\rangle, \langle u_2, 0.8\rangle, \langle u_3, 0.1\rangle\}$, $\Psi_1(g_3) = \{\langle u_1, 0.7\rangle, \langle u_2, 0.8\rangle, \langle u_3, 0.4\rangle\}$, $\Psi_1(g_4) = \{\langle u_1, 0.4\rangle, \langle u_2, 0.6\rangle, \langle u_3, 0.8\rangle\}$,
Software 2.0 $\gamma = (\chi, \mathcal{F}) = \Psi_2(g_1) = \{\langle u_1, 0.3\rangle, \langle u_2, 0.2\rangle, \langle u_3, 0.4\rangle\}$, $\Psi_2(g_2) = \{\langle u_1, 0.5\rangle,$

TABLE 2. The envisaged EN-based FHSS is compared with previous entropies.

SN	References	Entropies	Ranking
1	[59]	inaccurate assertion	×
2	[60]	inaccurate assertion	×
3	[61]	inaccurate assertion	×
4	[62]	inaccurate assertion	×
5	[64]	inaccurate assertion	×
6	[65]	inaccurate assertion	×
7	[66]	inaccurate assertion	×
8	[67]	inaccurate assertion	×
9	Proposed Method in this paper	$E(\psi,\mathcal{F})=6.2, E(\varphi,\mathcal{F})=6, E(\chi,\mathcal{F})=7.1$	$E(\varphi,\mathcal{F})\geq E(\psi,\mathcal{F})\geq E(\chi,\mathcal{F})$

$\langle u_2, 0.1\rangle, \langle u_3, 0.2\rangle\}$, $\Psi_2(g_3) = \{\langle u_1, 0.7\rangle, \langle u_2, 0.2\rangle, \langle u_3, 0.8\rangle\}$, $\Psi_2(g_4) = \{\langle u_1, 0.2\rangle, \langle u_2, 0.4\rangle, \langle u_3, 0.5\rangle\}$, Programming $\sigma = (\mu, \mathcal{F}) = \Psi_2(g_1'') = \{\langle u_1, 0.1\rangle, \langle u_2, 0.3\rangle, \langle u_3, 0.6\rangle\}$, $\Psi_2(g_2'') = \{\langle u_1, 0.1\rangle, \langle u_2, 0.4\rangle, \langle u_3, 0.6\rangle\}$, $\Psi_2(g_3'') = \{\langle u_1, 0.5\rangle, \langle u_2, 0.1\rangle, \langle u_3, 0.2\rangle\}$, $\Psi_2(g_4'') = \{\langle u_1, 0.4\rangle, \langle u_2, 0.6\rangle, \langle u_3, 0.2\rangle\}$, and ideal NT in the form of FHSS is $\zeta = (\psi, \mathcal{F}) = \Psi_2(g_1''') = \{\langle u_1, 0.4\rangle, \langle u_2, 0.6\rangle, \langle u_3, 0.1\rangle\}$, $\Psi_2(g_2''') = \{\langle u_1, 0.8\rangle, \langle u_2, 0.2\rangle, \langle u_3, 0.5\rangle\}$, $\Psi_2(g_3''') = \{\langle u_1, 0.4\rangle, \langle u_2, 0.3\rangle, \langle u_3, 0.9\rangle\}$, $\Psi_2(g_4''') = \{\langle u_1, 0.3\rangle, \langle u_2, 0.7\rangle, \langle u_3, 0.6\rangle\}$, By Definition 9, the Hamming distance between ξ and ζ is $d^H_{FHS}(\xi, \zeta) = \sum_{j=1}^{4}\sum_{i=1}^{3} |\Delta_{ij}u(x)| = 3.6$, $d^H_{FHS}(\gamma, \zeta) = \sum_{j=1}^{4}\sum_{i=1}^{3} |\Delta_{ij}u(x)| = 2.5$, $d^H_{FHS}(\sigma, \zeta) = \sum_{j=1}^{4}\sum_{i=1}^{3} |\Delta_{ij}u(x)| = 3.7$, and so, $S^H_{FHS}(\xi, \zeta) = \frac{1}{1+1.2} = 0.21$, $S^H_{FHS}(\gamma, \zeta) = \frac{1}{1+1.2} = 0.28$, $S^H_{FHS}(\sigma, \zeta) = \frac{1}{1+1.2} = 0.21$.

2) Thus, (γ, ζ) have highest SIM, so Software 2.0 is the most optimal NT source.

C. THE FHSS'S FEATURES AND A COMPARATIVE ANALYSIS

In the following subsection, we provide an evaluation of the introduced techniques considering their imperfections. This assessment aims to determine the feasibility and effectiveness of the proposed tricks. Additionally, we compare the envisioned NT with other existing systems and identify certain shortcomings. We discuss these drawbacks by illustrating the key concepts outlined in the relevant components.However, when features are further segmented into attribute values, all existing flaws fail to adapt. The concordance of organizational components is depicted; please see Table 3.

V. EVALUATIONS OF NEW TECHNOLOGIES USING A TOPSIS-BASED OPTIMIZED FHS SET CLASSIFIER

A. A CASESTUDY/PRACTICAL EXAMPLE

Environmental research is of utmost importance, particularly when it comes to the various aspects of NT. NT emerges as an inevitable consequence of domestic, enterprise, and organizational activities. To evaluate the options of New Technologies on a global scale, this section proposes a combined fuzzy Multiple Criteria Decision Making (MCDM) framework based on the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) approach. The framework takes into account specialized, contemporary factors related to social, institutional, innovation, economic, and ecological aspects. Through a detailed analysis, the evaluation aims to provide insights into the potential impact of NT on the environment.

B. THE EXPLORATION OF NEW TECHNOLOGIES RESOURCES AND ITS ASPECTS

Analytic NT exploration and machine learning mathematics significantly impact the environment as they can serve a significant role in the planning phase of the projects. The obtained insight will most likely be highly influential in the decision-making process involving numerous economic, social, and ecological factors. There are various kinds of NT that are explored. For more detail, please see figure 2. In recent years, several groundbreaking technologies have emerged, revolutionizing various industries. 3D Printing has enabled the creation of complex objects with precision and speed, transforming manufacturing processes. The advent of 6G internet promises lightning-fast connectivity, enabling seamless communication and powering the Internet of Things. Quantum Computing holds the potential to solve complex problems exponentially faster, revolutionizing fields like cryptography and drug discovery. Software 2.0 represents a paradigm shift in programming, utilizing machine learning and neural networks to create intelligent software systems. Artificial Intelligence has advanced significantly, empowering machines to mimic human intelligence and automate tasks across diverse domains. Programming remains a fundamental skill, allowing developers to create innovative software solutions. Automation and Robotics have gained prominence, enhancing efficiency and productivity across industries through autonomous systems. These technologies collectively shape the future, paving the way for

TABLE 3. Comparison of previous similarity measure to the proposed SIM.

SN	References	Sub-parameter	SIM	Ranking
1	[56]	×	inaccurate assertion	×
2	[57]	×	inaccurate assertion	×
3	[58]	×	inaccurate assertion	×
4	[68]	×	inaccurate assertion	×
10	[61]	×	inaccurate assertion	×
11	[69]	×	inaccurate assertion	×
16	[66]	×	inaccurate assertion	×
17	[65]	×	inaccurate assertion	×
18	[52]	×	inaccurate assertion	×
19	[51]	×	inaccurate assertion	×
20	Proposed Method	✓	$S_1 = 0.21$, $S_2 = 0.28$, $S_3 = 0.21$	$S_2 \geq S_1 \geq S_3$

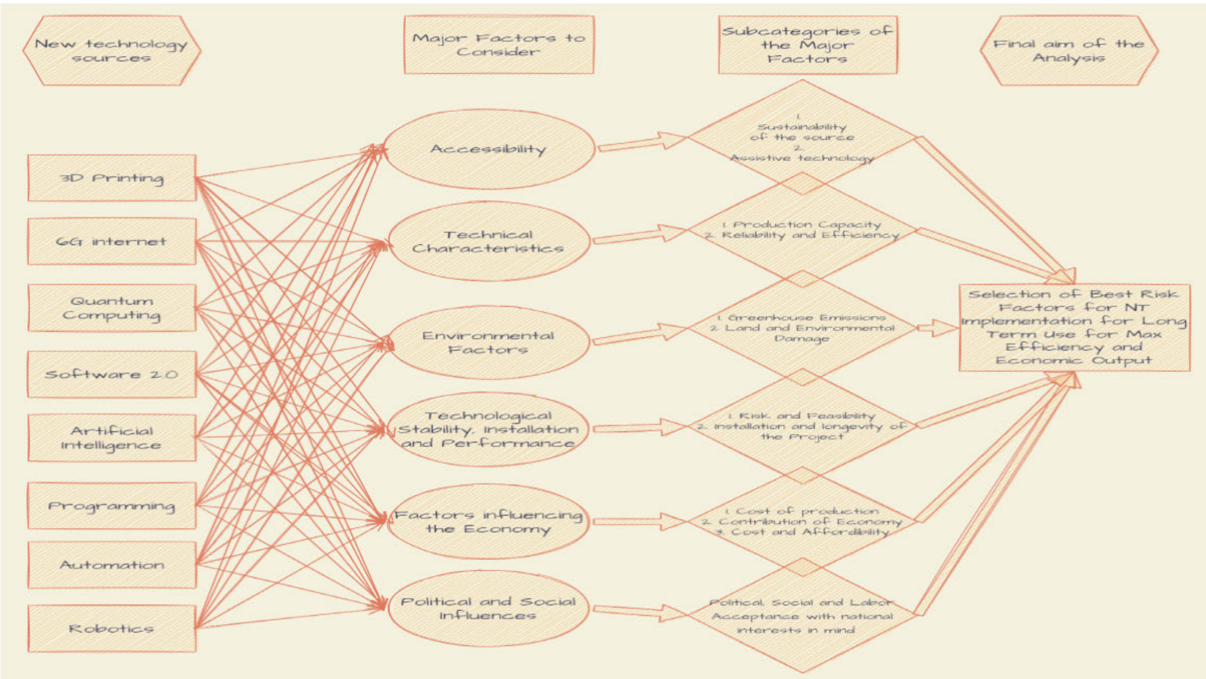

FIGURE 2. Flow chart for different NT resources.

TABLE 4. All experts opinions collectively.

Types of New Technologies/Criteria	1	2	3	4	5	6	7	8
3D Printing	0.04	0.98	0.78	0.41	0.22	0.54	0.31	0.8
6G internet	0.15	0.75	0.25	0.72	0.46	0.79	0.61	0.12
Quantum Computing	0.27	0.57	0.92	0.39	0.37	0.87	0.33	0.42
Software 2.0	0.52	0.12	0.24	0.58	0.51	0.42	0.63	0.71
Artificial Intelligence	0.83	0.99	0.42	0.21	0.39	0.62	0.61	0.64
Programming	0.11	0.71	0.66	0.89	0.38	0.87	0.48	0.62
Automation	0.63	0.67	0.78	0.06	0.6	0.07	0.89	0.38
Robotics	0.75	0.44	0.89	0.16	0.67	0.46	0.48	0.45

unprecedented advancements and transformative possibilities [5], [9], [10], [11], [12], [14], [15], [16].

- 3D Printing
- 6G internet
- Quantum Computing
- Software 2.0
- Artificial Intelligence
- Programming
- Automation
- Robotics

C. ALGORITHM

Step 1: To create a decision average matrix for each alternative based on the collective perspective of professionals in the FHS (Fuzzy Health System) set, we utilize the standardized precipitation fuzzy conceptual framework. This decision

TABLE 5. Normalized matrix.

Types of New Technologies/Criteria	1	2	3	4	5	6	7	8
3D Printing	0.028	0.49	0.41	0.28	0.16	0.30	0.19	0.50
6G internet	0.10	0.37	0.13	0.50	0.34	0.44	0.37	0.076
Quantum Computing	0.18	0.28	0.48	0.27	0.27	0.48	0.20	0.26
Software 2.0	0.36	0.060	0.12	0.40	0.38	0.23	0.39	0.45
Artificial Intelligence	0.58	0.49	0.22	0.14	0.29	0.34	0.37	0.40
Programming	0.07	0.35	0.34	0.62	0.28	0.48	0.29	0.39
Automation	0.44	0.33	0.41	0.042	0.45	0.039	0.55	0.24
Robotics	0.52	0.22	0.46	0.11	0.50	0.25	0.29	0.28

TABLE 6. Weighted normalized matrix.

Types of New Technologies/Criteria	1	2	3	4	5	6	7	8
3D Printing	0.0056	0.14	0.04	0.014	0.024	0.015	0.009	0.50
6G internet	0.021	0.11	0.13	0.0250	0.05	0.022	0.018	0.007
Quantum Computing	0.037	0.085	0.48	0.013	0.04	0.24	0.010	0.026
Software 2.0	0.07	0.018	0.12	0.020	0.05	0.011	0.19	0.45
Artificial Intelligence	0.11	0.14	0.022	0.007	0.044	0.017	0.018	0.040
Programming	0.015	0.010	0.0348	0.031	0.04	0.024	0.014	0.03
Automation	0.088	0.100	0.04	0.002	0.067	0.0019	0.02	0.02
Robotics	0.10	0.066	0.04	0.005	0.07	0.012	0.014	0.28

TABLE 7. Positive ideal solution.

C_1	0.116
C_2	0.148
C_3	0.048
C_4	0.031
C_5	0.075
C_6	0.024
C_7	0.027
C_8	0.05

TABLE 8. Negative ideal solution.

C_1	0.0056
C_2	0.018
C_3	0.012
C_4	0.0021
C_5	0.024
C_6	0.0019
C_7	0.0096
C_8	0.007

TABLE 9. Separation from positive ideal.

3D Printing	0.12
6G internet	0.11
Quantum Computing 2.0	0.11
Software 2.0	0.14
Artificial Intelligence	0.04
Programming	0.116
Automation	0.072
Robotics	0.09

matrix has been widely recognized in the field. To apply the TOPSIS, we need to rank the efficiency of each option using the following equation:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_1^m x_{ij}^2}}; \tag{1}$$

TABLE 10. Separation from negative ideal.

3D Printing	0.14
6G internet	0.10
Quantum Computing	0.09
Software 2.0	0.08
Artificial Intelligence	0.17
Programming	0.10
Automation	0.13
Robotics	0.12

TABLE 11. Preference values.

3D Printing	0.52
6G internet	0.46
Quantum Computing	0.44
Software 2.0	0.37
Artificial Intelligence	0.77
Programming	0.47
Automation	0.64
Robotics	0.58

with x = decision matrix; $i = 1, 2, \ldots, m$ and $j = 1, 2, \ldots, n$.

Step 2: Based on the weighted normalised rating (y_{ij}), the weighted normalised fuzzy control matrix can be computed as follows:

$$y_{ij} = w_i r_{ij} \tag{2}$$

with $i = 1, 2, \ldots, m$; and $j = 1, 2, \ldots, n$.

Step 3: To identify the best positive and negative solutions, we construct the positive ideal solution matrix and the negative ideal solution matrix. The positive ideal solution matrix is built using the equation(3), the negative ideal solution matrix is evaluated using the equation (4).

$$A^+ = (y_1^+, y_2^+, \ldots, y_n^+); \tag{3}$$

$$A^- = (y_1^-, y_2^-, \ldots, y_n^-); \tag{4}$$

TABLE 12. Final ranking matrix.

New Technologies/Criteria	1	2	3	4	5	6	7	8	Rank
3D Printing	0.04	0.98	0.78	0.41	0.22	0.54	0.31	0.8	4
6G internet	0.15	0.75	0.25	0.72	0.46	0.79	0.61	0.12	6
Quantum Computing	0.27	0.57	0.92	0.39	0.37	0.87	0.33	0.42	7
Software 2.0	0.52	0.12	0.24	0.58	0.51	0.42	0.63	0.71	8
Artificial Intelligence	0.83	0.99	0.42	0.21	0.39	0.62	0.61	0.64	1
Programming	0.11	0.71	0.66	0.89	0.38	0.87	0.48	0.62	5
Automation	0.63	0.67	0.78	0.06	0.6	0.07	0.89	0.38	2
Robotics	0.75	0.44	0.89	0.16	0.67	0.46	0.48	0.45	3

Step 4: The distance between each attributic value of each renewable energy source for each criterion and both positive and negative ideal solution must be calculated in the next step. The distance between alternative A_i and the positive ideal solution can be demonstrated as equation (5):

$$D^+ = \sqrt{\sum_{j=1}^{n} (y_i^+ - y_{ij})^2}; \tag{5}$$

$i = 1, 2, 3 \ldots m$ The distance between alternative A_i with negative ideal solution can be formulated with equation (4):

$$D^- = \sqrt{\sum_{j=1}^{n} (y_i^- - y_{ij})^2}; \tag{6}$$

$i = 1, 2, 3 \ldots m$

Step 5: Determining the value of preference for each alternative The preference value for each alternative (V_i) is given as:

$$V_i = \frac{D_i^-}{D_i^- + D_i^+} \tag{7}$$

$i = 1, 2, 3 \ldots m$

Step 6: Sort the options and select the best one.

D. NUMERICAL EXAMPLE

Step 1: Let $X = \{a$ =3D Printing, b = 6G internet, c =Quantum Computing, d =Software 2.0, e =Artificial Intelligence, f =Programming, g =Automation, h = Robotics }, be a set of alternatives and $\{\delta_1, \delta_2, \delta_3, \delta_4\}$ is a set of experts who will evaluate the best alternative with weight vector $(0.2, 0.3, 0.1, 0.05, 0.15, 0.05, 0.05, 0.1)^T$, let a_1 = Environmental, a_2 = Ubiquity, a_3 = Economic, be distinct features with respective feature values that are collections main components Q_1, Q_2, Q_3, let $Q_1 = \{\eta_1$ = Depletion of natural resources, η_2 = Smart Technology, η_3 = Need of waste disposal, η_4 = Environmental damage$\}$, $Q_2 = \{\eta_5$ = flexible and proactive, η_6 = Sustainability$\}$, $Q_3 = \{\eta_7$ = Affordability$\}$, where $Q_1 \times Q_2 \times Q_3 = \{C_i, i = 1, 2, 3, \ldots 8\}$. In collaboration with experts, we have developed a decision average matrix for each alternative based on the collective opinions of experts in the FHS set. This matrix is created by considering a set of parameters and their respective sub-parameter values, please see Table 4. Normalized Table 5 by using Equation (1).

Step 2: By utilizing Equation (2), it is possible to develop a weighted decision matrix for each alternatives, see Table 6.

Step 3: Compute the positive ideal solution and negative ideal solution using Equations (3) and (4), respectively, see Tables 7,8.

Step 4: Compute the distance of each candidate from positive and negative ideal solution using Equations (5) and (6), see Tables 9,10.

Step 5: Compute the preference value for each alternative using Equation (7), see Table 11.

Step 6: Rank the alternatives and choose the best one, see Table 12.

VI. CONCLUSION

In conclusion, the increasing population and technological advancements have led to a growing demand for new technologies (NT) worldwide. However, traditional technologies are proving to be insufficient in meeting these requirements. Therefore, it is crucial to explore cost-effective and environmentally friendly green technologies as a response to this resource crisis. The future direction lies in the development and implementation of emerging technologies such as connectivity (5G, 6G), programming, artificial intelligence, and renewable energy solutions. The paper proposes extended Multi-Criteria Decision Making (MCDM) strategies to optimize implementation associated with new technologies. The novel approach of using Fuzzy Hypersoft (FHS) set is discussed, which can effectively handle uncertainties, vagueness, and unclear data. This framework offers greater flexibility compared to existing literature structures by allowing for sub-partitioning of attribute values, resulting in a better understanding of the information. In the assessment of criteria for energy options, precise figures may not always be available, necessitating the use of human and expert judgments. This adaptable and sensitive review approach ensures a more comprehensive analysis. The adaptive MCDM design incorporating Entropy (EN), Similarity Measure (SIM), and TOPSIS techniques relies on the FHS framework. These frameworks are particularly valuable for investigating renewable energy (RE) issues as they can handle a wide range of attributes, including components with multiple sub-attribute values. To demonstrate the practical application of the proposed approach, expert ratings are utilized. This showcases the relevance and effectiveness of the methodology. Furthermore, a sensitivity analysis is conducted to assess the impact of primary criterion weights in the sorting process. Moving forward, the research should focus on implementing and testing the proposed MCDM strategies and the Fuzzy Hypersoft set in real-world scenarios. Practical experiments and case studies can provide valuable insights and validate the effectiveness of the approach. Additionally, the framework could be expanded to include other relevant factors and criteria, considering the evolving nature of technology and environmental challenges. As a future research suggestion, various integrated fuzzy Multiple Criteria Decision Making (MCDM) techniques such as Neutrosophic Hypersoft Set, Plithogenic Hypersoft Set, Pythagorean fuzzy uncertainty, Hypersoft Set, and Plithogenic Intuitionistic FHS (Fuzzy Health System) Set, along with their hybrid structures, can be applied to address a range of problems. These methodologies have the potential to deliver desired outcomes and provide valuable insights.

In particular, these techniques can find applications in fields like medical imaging problems, image processing, and pattern recognition studies. Their utilization in these areas can contribute to advancements and improvements in various aspects, including diagnostic accuracy, image enhancement, and object classification.

REFERENCES

[1] T. L. Saaty, *Multicriteria Decision Making: The Analytic Hierarchy Process*. Pittsburgh, PA, USA: RWS Publications, 1990.

[2] S. B. Kim and K. S. Whang, "Forecasting the capabilities of Korean civil aircraft industry," *Omega*, vol. 21, no. 1, pp. 91–98, 1993.

[3] C. H. Cheng, "Evaluating naval tactical missile systems by fuzzy AHP based on the grade value of membership function," *Eur. J. Oper. Res.*, vol. 96, pp. 343–350, Jan. 1996.

[4] M. An, C. Baker, and J. Zeng, "A fuzzy-logic-based approach to qualitative risk modelling in the construction process," *World J. Eng.*, vol. 2, no. 1, pp. 1–12, 2005.

[5] D. C. Nguyen, M. Ding, P. N. Pathirana, A. Seneviratne, J. Li, D. Niyato, O. Dobre, and H. V. Poor, "6G Internet of Things: A comprehensive survey," *IEEE Internet Things J.*, vol. 9, no. 1, pp. 359–383, Jan. 2022.

[6] G. M. Winch, *Managing Construction Projects: An Information Processing Approach*. Oxford, U.K.: Blackwell Science, 2002.

[7] H. Zhi, "Risk management for overseas construction," *Int. J. Project Manag.*, vol. 13, pp. 231–237, Aug. 1995.

[8] J. Zeng, M. An, A. H. C. Chan, and Y. Lin, "A methodology for assessing risks in the construction process," in *Proc. 20th Annu. Conf.*, F. Khosrowshahi, Ed. Edinburgh, U.K.: Association of Researchers in Construction Management (ARCOM), 2004, pp. 1165–1174.

[9] (2018). *David, MX3D to Install World's First 3D Printed Steel Bridge Over Amsterdam Canal 3D Printer and 3D Printing News*. [Online]. Available: https://www.3ders.org/articles/20180403-mx3d-to-install-worlds-first-3d-printed-steel-bridge-over-amsterdam-canal.html

[10] M. Dilhara, A. Ketkar, and D. Dig, "Understanding software-2.0: A study of machine learning library usage and evolution," *ACM Trans. Softw. Eng. Methodol.*, vol. 30, no. 4, pp. 1–42, 2021.

[11] P. Hamet and J. Tremblay, "Artificial intelligence in medicine," *Metabolism*, vol. 69, pp. S36–S40, Apr. 2017.

[12] A. Steane, "Quantum computing," *Rep. Prog. Phys.*, vol. 61, no. 2, p. 117, 1998.

[13] H. Srikanth, C. Hettiarachchi, and H. Do, "Requirements based test prioritization using risk factors: An industrial study," *Inf. Softw. Technol.*, vol. 69, pp. 71–83, Jan. 2016.

[14] A. Robins, J. Rountree, and N. Rountree, "Learning and teaching programming: A review and discussion," *Comput. Sci. Educ.*, vol. 13, no. 2, pp. 137–172, Mar. 2003.

[15] E. Garcia, M. A. Jimenez, P. G. D. Santos, and M. Armada, "The evolution of robotics research," *IEEE Robot. Autom. Mag.*, vol. 14, no. 1, pp. 90–103, Mar. 2007.

[16] L. Bainbridge, "Ironies of automation," in *Analysis, Design and Evaluation of Man-Machine Systems*. Amsterdam, The Netherlands: Elsevier, 1983, pp. 129–135.

[17] V. L. B. Viana and M. T. M. Carvalho, "Prioritization of risks related to BIM implementation in Brazilian public agencies using fuzzy logic," *J. Building Eng.*, vol. 36, Apr. 2021, Art. no. 102104.

[18] T. Patterson, S. Esteves, R. Dinsdale, and A. Guwy, "Life cycle assessment of biogas infrastructure options on a regional scale," *Bioresource Technol.*, vol. 102, no. 15, pp. 7313–7323, Aug. 2011.

[19] J. L. Sawin, E. Martinot, B. Sonntag, A. McCrone, J. Roussell, D. Barnes, and C. Flavin, "Renewables 2010 global status report," Int. Nucl. Inf. Syst., France, Tech. Rep. INIS-FR–15-0648, 2010, vol. 46, no. 38.

[20] D. A. Haralambopoulos and H. Polatidis, "Renewable energy projects: Structuring a multi-criteria group decision-making framework," *Renew. Energy*, vol. 28, no. 6, pp. 961–973, May 2003.

[21] M. Beccali, M. Cellura, and M. Mistretta, "Decision-making in energy planning. Application of the electre method at regional level for the diffusion of renewable energy technology," *Renew. Energy*, vol. 28, no. 13, pp. 2063–2087, Oct. 2003.

[22] K. Nigim, N. Munier, and J. Green, "Pre-feasibility MCDM tools to aid communities in prioritizing local viable renewable energy sources," *Renew. Energy*, vol. 29, no. 11, pp. 1775–1791, Sep. 2004.

[23] R. Madlener, K. Kowalski, and S. Stagl, "New ways for the integrated appraisal of national energy scenarios: The case of renewable energy use in Austria," *Energy Policy*, vol. 35, no. 12, pp. 6060–6074, Dec. 2007.

[24] K. Kowalski, S. Stagl, R. Madlener, and I. Omann, "Sustainable energy futures: Methodological challenges in combining scenarios and participatory multi-criteria analysis," *Eur. J. Oper. Res.*, vol. 197, no. 3, pp. 1063–1074, Sep. 2009.

[25] M. Troldborg, S. Heslop, and R. L. Hough, "Assessing the sustainability of renewable energy technologies using multi-criteria analysis: Suitability of approach for national-scale assessments and associated uncertainties," *Renew. Sustain. Energy Rev.*, vol. 39, pp. 1173–1184, Nov. 2014.

[26] M. Kabak and M. Dağdeviren, "Prioritization of renewable energy sources for Turkey by using a hybrid MCDM methodology," *Energy Convers. Manag.*, vol. 79, pp. 25–33, Mar. 2014.

[27] C. Kahraman, I. Kaya, and S. Cebi, "A comparative analysis for multiattribute selection among renewable energy alternatives using fuzzy axiomatic design and fuzzy analytic hierarchy process," *Energy*, vol. 34, no. 1, pp. 1603–1634, 2009.

[28] C. Kahraman, S. Cebi, and I. Kaya, "Selection among renewable energy alternatives using fuzzy axiomatic design: The case of Turkey," *J. Comput. Sci.*, vol. 16, no. 1, pp. 82–102, 2010.

[29] T. Kaya and C. Kahraman, "Multicriteria renewable energy planning using an integrated fuzzy VIKOR & AHP methodology: The case of Istanbul," *Energy*, vol. 35, no. 6, pp. 2517–2527, Jun. 2010.

[30] A. Sadeghi, T. Larimian, and A. Molabashi, "Evaluation of renewable energy sources for generating electricity in province of Yazd: A fuzzy MCDM approach," *Proc.-Social Behav. Sci.*, vol. 62, pp. 1095–1099, Oct. 2012.

[31] T. Ertay, C. Kahraman, and İ. Kaya, "Evaluation of renewable energy alternatives using MACBETH and fuzzy AHP multicriteria methods: The case of Turkey," *Technol. Econ. Develop. Economy*, vol. 19, no. 1, pp. 38–62, Apr. 2013.

[32] A. Tasri and A. Susilawati, "Selection among renewable energy alternatives based on a fuzzy analytic hierarchy process in Indonesia," *Sustain. Energy Technol. Assessments*, vol. 7, pp. 34–44, Sep. 2014.

[33] G. Büyüközkan and S. Güleryüz, "A new GDM based AHP framework with linguistic interval fuzzy preference relations for renewable energy planning," *J. Intell. Fuzzy Syst.*, vol. 27, no. 6, pp. 3181–3195, 2014.

[34] A. Balin and H. Baraçli, "A fuzzy multi-criteria decision making methodology based upon the interval type-2 fuzzy sets for evaluating renewable energy alternatives in Turkey," *Technol. Econ. Develop. Economy*, vol. 23, no. 5, pp. 742–763, Sep. 2015.

[35] P. Adhikary, P. K. Roy, and A. Mazumdar, "Optimal renewable energy project selection: A multi-criteria optimization technique approach," *Global J. Pure Appl. Math.*, vol. 11, no. 5, pp. 3319–3329, 2015.

[36] G. Büyüközkan and S. Güleryüz, "An integrated DEMATEL-ANP approach for renewable energy resources selection in Turkey," *Int. J. Prod. Econ.*, vol. 182, pp. 435–448, Dec. 2016.
[37] H. Al Garni, A. Kassem, A. Awasthi, D. Komljenovic, and K. Al-Haddad, "A multicriteria decision making approach for evaluating renewable power generation sources in Saudi Arabia," *Sustain. Energy Technol. Assessments*, vol. 16, pp. 137–150, Aug. 2016.
[38] Y. Çelikbilek and F. Tüysüz, "An integrated grey based multi-criteria decision making approach for the evaluation of renewable energy sources," *Energy*, vol. 115, pp. 1246–1258, Nov. 2016.
[39] L. A. Zadeh, "Fuzzy sets," *Inf. Control*, vol. 8, no. 3, pp. 338–353, 1965.
[40] D. Molodtsov, "Soft set theory first results," *Comput. Math. With Appl.*, vol. 37, nos. 4–5, pp. 19–31, 1999.
[41] Y. Y. Yao, "Relational interpretations of neighborhood operators and rough set approximation operators," *Inf. Sci.*, vol. 111, nos. 1–4, pp. 239–259, 1998.
[42] H. Thielle, "On the concepts of qualitative fuzzy sets," in *Proc. ISMVL*, Nursultan, Kazakhstan, 1999, pp. 282–287.
[43] P. K. Maji, R. Biswas, and A. R. Roy, "Fuzzy soft sets," *J. Fuzzy Math.*, vol. 9, no. 3, pp. 589–602, 2001.
[44] P. K. Maji, A. R. Roy, and R. Biswas, "An application of soft sets in a decisionmaking problem," *Comput. Math. Appl.*, vol. 44, nos. 8–9, pp. 1077–1083, 2002.
[45] Y. Yang, X. Tan, and C. Meng, "The fuzzy soft set and its application in decision making," *Appl. Math. Model.*, vol. 37, no. 7, pp. 4915–4923, 2013.
[46] L. A. Zadeh, "Probability measures of fuzzy events," *J. Math. Anal. Appl.*, vol. 23, no. 2, pp. 199–212, 1984.
[47] A. D. Luca and S. A. Termini, "A definition of a nonprobabilistic entropy in the setting of fuzzy sets theory," *Inf. Control*, vol. 20, no. 4, pp. 301–312, 1972.
[48] H. Zhang, W. Zhang, and C. Mei, "Entropy of interval-valued fuzzy sets based on distance and its relationship with similarity measure," *Knowl.-Based Syst.*, vol. 22, no. 6, pp. 449–454, Aug. 2009.
[49] M. Saeed, M. Saqlain, A. Mehmood, K. Naseer, and S. Yaqoob, "Multi-polar neutrosophic soft sets with application in medical diagnosis and decision-making," *Neutrosophic Sets Syst.*, vol. 33, no. 1, pp. 183–207, 2020.
[50] P. Muthukumar and G. S. S. Krishnan, "A similarity measure of intuitionistic fuzzy soft sets and its application in medical diagnosis," *Appl. Soft Comput.*, vol. 41, pp. 148–156, Apr. 2016.
[51] Y. Al-Qudah and N. Hassan, "Operations on complex fuzzy sets," *J. Intell. Fuzzy. Syst.*, vol. 33, no. 3, pp. 1527–1540, 2017.
[52] Y. Al-Qudah and N. Hassan, "Complex multi-fuzzy soft set: Its entropy and similarity measure," *IEEE Access*, vol. 6, pp. 65002–65017, 2018.
[53] Z. Liu, K. Qin, and Z. Pei, "Similarity measure and entropy of fuzzy soft sets," *Sci. World J.*, vol. 2014, no. 1, 2014, Art. no. 161607.
[54] F. Smarandache, "Extension of soft set to hypersoft set and then to plithogenic hypersoft set," *Neutrosophic Set Syst.*, vol. 22, no. 1, pp. 168–170, 2018.
[55] M. Saeed, M. Ahsan, M. S. Khubab, and M. R. Ahmad, "A study of the fundamentals of hypersoft set theory," *Int. Sci. Eng.*, vol. 11, no. 1, pp. 320–329, 2020.
[56] Y. Li, D. L. Olson, and Z. Qin, "Similarity measures between intuitionistic fuzzy (vague) sets: A comparative analysis," *Pattern Recognit. Lett.*, vol. 28, no. 2, pp. 278–285, Jan. 2007.
[57] S.-M. Chen, "Similarity measures between vague sets and between elements," *IEEE Trans. Syst. Man, Cybern. B, Cybern.*, vol. 27, no. 1, pp. 153–158, Feb. 1997.
[58] S.-M. Chen, S.-H. Cheng, and T.-C. Lan, "A novel similarity measure between intuitionistic fuzzy sets based on the centroid points of transformed fuzzy numbers with applications to pattern recognition," *Inf. Sci.*, vols. 343–344, pp. 15–40, May 2016.
[59] E. Szmidt and J. Kacprzyk, "Entropy for intuitionistic fuzzy sets," *Fuzzy Sets Syst.*, vol. 118, no. 3, pp. 467–477, Mar. 2001.
[60] P. Majumdar and S. K. Samanta, "On similarity and entropy of neutrosophic sets," *J. Intell. Fuzzy Syst.*, vol. 26, no. 3, pp. 1245–1252, 2014.
[61] J. Ye and S. Du, "Some distances, similarity and entropy measures for interval-valued neutrosophic sets and their relationship," *Int. J. Mach. Learn. Cybern.*, vol. 10, no. 2, pp. 347–355, Feb. 2019.
[62] A. Aydoğdu, "On entropy and similarity measure of interval valued neutrosophic sets," *Neutrosophic Sets Syst.*, vol. 9, pp. 47–49, Jan. 2015.
[63] M. Saeed, M. Ahsan, and A. U. Rahman, "A theoretical and analytical approach for fundamental framework of composite mappings on fuzzy hypersoft classes," *Neutrosophic Set Syst.*, vol. 45, no. 1, pp. 268–285, 2021.
[64] T. M. Athira, S. J. John, and H. Garg, "Entropy and distance measures of Pythagorean fuzzy soft sets and their applications," *J. Intell. Fuzzy Syst.*, vol. 37, no. 3, pp. 4071–4084, Oct. 2019.
[65] L. Bi, Z. Zeng, B. Hu, and S. Dai, "Two classes of entropy measures for complex fuzzy sets," *Mathematics*, vol. 7, no. 1, p. 96, Jan. 2019.
[66] T. Kumar and R. K. Bajaj, "On complex intuitionistic fuzzy soft sets with distance measures and entropies," *J. Math.*, vol. 2014, no. 1, 2014, Art. no. 972198.
[67] G. Selvachandran, H. Garg, and S. Quek, "Vague entropy measure for complex vague soft sets," *Entropy*, vol. 20, no. 6, p. 403, May 2018.
[68] W.-L. Hung and M.-S. Yang, "Similarity measures of intuitionistic fuzzy sets based on Hausdorff distance," *Pattern Recognit. Lett.*, vol. 25, no. 14, pp. 1603–1611, Oct. 2004.
[69] G. W. Wei, "Some similarity measures for picture fuzzy sets and their applications," *Iranian J. Fuzzy Syst.*, vol. 15, no. 1, pp. 77–89, 2018.
[70] M. Abbas, G. Murtaza, and F. Smarandache, "Basic operations on hypersoft sets and hypersoft point," *Neutrosophic Set Syst.*, vol. 35, no. 1, pp. 407–421, 2020.
[71] M. Saeed, M. Ahsan, and A. U. Rahman, "A novel approach to mappings on hypersoft classes with application, in *Theory and Application of Hypersoft Set*. Brussels, Belgium: Pons Publication House, 2021, pp. 175–191.
[72] M. Saeed, M. Ahsan, A. U. Rahman, and F. Smarandache, "An inclusive study on fundamentals of hypersoft set," in *Theory and Application of Hypersoft Set*. Brussels, Belgium: Pons Publication House, 2021, pp. 1–23.
[73] M. Ahsan, M. Saeed, A. Mehmood, M. H. Saeed, and J. Asad, "The study of HIV diagnosis using complex fuzzy hypersoft mapping and proposing appropriate treatment," *IEEE Access*, vol. 9, pp. 104405–104417, 2021.
[74] M. Saeed, M. Ahsan, A. U. Rahman, M. H. Saeed, and A. Mehmood, "An application of neutrosophic hypersoft mapping to diagnose brain tumor and propose appropriate treatment," *J. Intell. Fuzzy Syst.*, vol. 41, no. 1, pp. 1677–1699, Aug. 2021.
[75] M. Saeed, M. Ahsan, M. H. Saeed, A. Mehmood, and T. Abdeljawad, "An application of neutrosophic hypersoft mapping to diagnose hepatitis and propose appropriate treatment," *IEEE Access*, vol. 9, pp. 70455–70471, 2021.
[76] M. Saeed, M. Ahsan, A. Mehmood, M. H. Saeed, and J. Asad, "Infectious diseases diagnosis and treatment suggestions using complex neutrosophic hypersoft mapping," *IEEE Access*, vol. 9, pp. 146730–146744, 2021.
[77] M. Saeed, M. Ahsan, M. H. Saeed, A. Mehmood, and S. El-Morsy, "Assessment of solid waste management strategies using an efficient complex fuzzy hypersoft set algorithm based on entropy and similarity measures," *IEEE Access*, vol. 9, pp. 150700–150714, 2021.
[78] U. M. Modibbo, M. Hassan, A. Ahmed, and I. Ali, "Multi-criteria decision analysis for pharmaceutical supplier selection problem using fuzzy TOPSIS," *Manag. Decis.*, vol. 60, no. 3, pp. 806–836, Feb. 2022.
[79] F. Xiao, J. Wen, and W. Pedrycz, "Generalized divergence-based decision making method with an application to pattern classification," *IEEE Trans. Knowl. Data Eng.*, vol. 35, no. 7, pp. 6941–6956, Jul. 2022.

MUHAMMAD AHSAN received the B.Sc. degree in mathematics from Punjab University, Pakistan, the M.Sc. degree in applied mathematics from GC University Faisalabad, Pakistan, the M.Phil. degree from Riphah International University, Islamabad, Pakistan, and the Ph.D. degree from the University of Management and Technology, Pakistan. Currently, he holds the position of an assistant professor at Riphah International University, Faisalabad, Pakistan, while also serving as a visiting researcher at the University of Management and Technology, Lahore, Pakistan. In recent times, he has taken on the responsibility of supervising a group of 11 master's students. Moreover, his academic contributions are quite remarkable, with 15 articles authored by him and his participation in two book chapters, all published in esteemed journals. His research area primarily focuses on decision making, fuzzy sets, soft sets, hypersoft sets, fuzzy hypersoft sets, and complex fuzzy hypersoft sets.

MUHAMMAD AMAD SARWAR was born in Pakistan. He received the degree from the University of Gujrat, and the M.S. degree from the University of Management and Technology, Lahore, Pakistan. He is currently pursuing the Ph.D. degree in mathematics with the Nanjing University of Aeronautics and Astronautics, Nanjing, China. His research interests include fuzzy mathematics, algebraic and hybrid structures of soft sets and hypersoft sets, multicriteria decision making, optimizations, renewable energy, artificial intelligence, graph theory in fuzzy-like, soft-like, hypersoft-like environments, and similarity and distance measures.

SHOWKAT AHMAD LONE was born in Wadwan, Budgam, Jammu and Kashmir, India. He received the M.Sc. degree in statistics from the University of Kashmir, in 2013, and the Ph.D. degree in statistics (reliability engineering) from Aligarh Muslim University, India, in 2017. He is currently an Associate Professor of mathematics and statistics with Saudi Electronic University (SEU), Saudi Arabia. His research interests include statistics and reliability engineering.

SALMEH A. ALMUTLAK was with the Research Department, Central Bank of Jordan (CBJ), for 23 years, from 1992 to 2015, as the Head of the Macroeconometric Modeling Division. She was a part-time teaching with several universities and institutes, including The University of Jordan. She was with the Public Administration Institute in the field of teaching and training, Riyadh, from 2009 to 2011. She was with the Ministry of Social Development. She has been an Assistant Professor of mathematics and statistics with Saudi Electronic University, Riyadh, since 2014. She participated in many official missions, such as committees, seminars, workshops, and conferences at the local and international level, especially on the topics of statistical work and economic and social statistics, including national accounts and balance of payments statistics, financial and monetary statistics, labor statistics, gender, poverty, and other areas of development. Participated in many other statistical missions as a statistical expert in the regional workshop on the GSBPM. Participated in training with local and international fields, such as the training on national income accounts and quantitative methods financial analysis and the methods of scientific research using SPSS software, economic analysis and forecasting using Eviews. She is a member of the National Committee for the Construction of Models of the General Balance of the Jordanian Economy and a member of the Project for Scenarios for Jordan 2030.

SADIA ANWER received the Ph.D. degree in statistics from Aligarh Muslim University, India, in 2015. She is currently an Assistant Professor with the Department of Mathematics, Prince Sattam bin Abdulaziz University, Saudi Arabia. Her research interests include statistics and its application areas, such us reliability testing, statistical modeling, survival analysis, and statistical inference.