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ARTICLE

Fully Completed Spherical Fuzzy Approach-Based Z Numbers (PHI Model) for Enhanced Group Expert Consensus

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ABSTRACT

This study aims to establish an expert consensus and enhance the efficacy of decision-making processes by integrating Spherical Fuzzy Sets (SFSs) and Z-Numbers (SFZs). A novel group expert consensus technique, the PHI model, is developed to address the inherent limitations of both SFSs and the traditional Delphi technique, particularly in uncertain, complex scenarios. In such contexts, the accuracy of expert knowledge and the confidence in their judgments are pivotal considerations. This study provides the fundamental operational principles and aggregation operators associated with SFSs and Z-numbers, encompassing weighted geometric and arithmetic operators alongside fully developed operators tailored for SFZs numbers. Subsequently, a case study and comparative analysis are conducted to illustrate the practicality and effectiveness of the proposed operators and methodologies. Integrating the PHI model with SFZs numbers represents a significant advancement in decision-making frameworks reliant on expert input. Further, this combination serves as a comprehensive tool for decision-makers, enabling them to achieve heightened levels of consensus while concurrently assessing the reliability of expert contributions. The case study results demonstrate the PHI model's utility in resolving complex decision-making scenarios, showcasing its ability to improve consensus-building processes and enhance decision outcomes. Additionally, the comparative analysis highlights the superiority of the integrated approach over traditional methodologies, underscoring its potential to revolutionize decision-making practices in uncertain environments.

KEYWORDS

Spherical fuzzy sets; Delphi method; Z-numbers; expert consensus; PHI model; uncertainty

1 Introduction

Recently, numerous scholars have focused on studying the representation of uncertain information, and one notable approach is the utilization of fuzzy set theory, which employs membership degrees (MD) to capture uncertainty. Many extended models have been developed based on classic fuzzy sets. Zadeh [1] introduced the idea of Fuzzy Sets (FSs) in 1965. The concept of FS is to use an MD (α with $\alpha \in [0, 1]$) to evaluate criteria. In several circumstances, the FSs cannot handle knowledge supplied to a person through truth and falsity grades. Therefore, Atanassov [2] developed the theory of Intuitionistic Fuzz Sets (IFSs) by adding the term of a non-membership degree (NMD) denoted by β such that $\beta \in [0, 1]$. IFS is a comprehensive and robust strategy for dealing with complicated and unreliable data in decision-making settings. Numerous scholars indicated that IFS is a more comprehensive and robust strategy for dealing with complex and unreliable data in decision-making settings than FS. IFS theory has been used by many scholars in various fields [3,4]. However, the IFS cannot handle this if someone offers such values; the sum of MD and NMD exceeds the unit interval. Therefore, based on the weakness of IFS, Yager et al. [5] introduced the concept of Pythagorean fuzzy sets (PyFSs), which have a more flexible condition because they take the square of MD and NMD with $\alpha + \beta \in [0, 1]$. Due to the flexible conditions of objects, PyFSs can reduce information loss and are widely used by many scholars in various business fields [6,7]. However, if the square of MD and NMD exceeds 1, PyFs cannot handle this object. This is the reason why Yager [8] continuously developed the q-Rung Orthopair Fuzzy Sets (qROFs) with the restriction that the sum of the q-powers for the MD and NMD cannot be greater than the unit interval ($\alpha^q + \beta^q \in [0, 1], q \in Z^+$). The q-ROFS has received much use and has attracted more interest from researchers because of its structure [9,10].

While q-ROF offers notable advantages, researchers may encounter challenges when assessing information. In numerous real-life scenarios, MD and NMD may fall short in accurately expressing information, often due to instances of abstention and refusal, similar to situations encountered in voting or collecting human opinions. Cuong et al. [11] proposed the Picture Fuzzy Sets (PFSs) to overcome these problems with four degrees, i.e., MD, NMD, an abstinence degree (AD), and refusal degree (RD), with the condition ($\alpha + \beta + \gamma \in [0, 1]$), where MD, AD, and NMD are denoted by $\alpha, \beta, and\ \gamma$, respectively. PFS is a more robust method of handling complex and unreliable information in decision-making difficulties. Since its debut, PFS has drawn the fascination of numerous works [12,13]. Although PFSs can find more information loss than IFSs, PyFs, and q-ROFs, PFSs still have MD, AD, and NMD limitations, making it impossible for decision-makers to voice their opinions independently. Kutlu Gündoğdu et al. [14] recognized this problem and suggested an extension of PFS known as Spherical Fuzzy Sets (SFSs), such that the total of the squares of the MD, AD, and NMD is confined to [0,1] (or $\alpha^2 + \beta^2 + \gamma^2 \in [0, 1]$). Compared to PFS, DEs in SFS have more discretion when making decisions. SFSs is currently a helpful tool for evaluating information and has been used in several domains [15]. Since SFSs were introduced, they have attracted the attention of many researchers. Ashraf et al. [16] developed spherical fuzzy t'-norms and spherical fuzzy t'-conorms. It also presented a spherical fuzzy negator and several classes of spherical fuzzy t'-norms and t-conorms, which help develop the aggregation operator that aggregates the spherical fuzzy data. Ali et al. [17] proposed the complex spherical fuzzy Bonferroni mean (CSFBM) and complex spherical fuzzy weighted Bonferroni mean (CSFWBM) operators based on complex spherical fuzzy sets (CSFSs), integrating with the Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) to examine the suggested procedures. Güner et al. [18] presented the generalized spherical fuzzy sets application of a notion about aggregation operators from SFSs by introducing Einstein sum, product, and scalar multiplication based on Einstein's triangular norm and conorm. Ashraf et al. [19] developed Spherical fuzzy Dombi weighted averaging (SFDWA), Spherical fuzzy Dombi ordered weighted averaging (SFDOWA), Spherical fuzzy Dombi hybrid weighted averaging (SFDHWA), Spherical fuzzy Dombi weighted geometric (SFDWG), Spherical fuzzy Dombi ordered weighted geometric (SFDOWG), and Spherical fuzzy Dombi hybrid weighted geometric (SFDHWG) aggregation operators and discuss several properties of these aggregation operators. Furthermore, SFSs are usually combined with the MCDM method due to its advantages. Kutlu Gündoğdu et al. [14] extended traditional Weighted Aggregated Sum Product Assessment (WASPAS), VIseKriterijumska Optimizacija I KOmpromisno Resenje (VIKOR), Analytic Hierarchy Process (AHP), and TOPSIS methods to spherical fuzzy WASPAS (SF-WASPAS), spherical fuzzy VIKOR (SF-VIKOR), spherical fuzzy AHP (SF-AHP), and spherical fuzzy TOPSIS (SF-TOPSIS) methods to deal with the complexity of MCDM problems.

Drawing upon an extensive literature review, this study highlights a significant gap in the current decision-making methodologies, particularly in MCDM. The intrinsic challenge lies in the imperfect nature of available information, characterized by its ambiguity, unreliability, and partiality [18]. While conventional fuzzy numbers offer a mechanism for grappling with uncertainty, they often overlook the crucial aspect of certainty within the data [19]. Addressing this shortfall, Z-numbers emerge as a promising avenue, providing a more nuanced portrayal of incomplete information [20]. These Z-numbers, represented as Z (A, R), encapsulate two critical components: A, denoting the variable limitation, and R, signifying the reliability degree. This conceptualization presents a more profound and adaptable framework for formalizing the intricacies of decision-making processes [21]. As interpreted by Nguyen et al. [22], the Z number generalizes real, interval, random, and fuzzy numbers, thus offering a heightened level of effectiveness in modeling real-world systems. The versatility of Z-number theory extends to its ability to accurately encapsulate incomplete information in a manner akin to natural language expressions [20]. However, the prevailing Delphi method, whether traditional or spherical fuzzy, often falters in adequately factoring in the reliability of expert opinions, thereby jeopardizing the integrity of analysis outcomes. For instance, Mohandes et al. [23] constructed a Pentagonal Fuzzy Delphi Method (PFDM) to determine possible causes of associated accidents on building sites. Similarly, Nguyen's work utilized the SF-Delphi technique to establish expert consensus on the criteria governing employee satisfaction in the logistics service sector. [24], as well as to validates critical criteria influencing Vietnamese customers' apartment selection [25].

Nevertheless, both traditional Delphi and SF-Delphi models ignore the inherent uncertainty surrounding expert opinions, which can significantly sway analysis results and influence [22]. Therefore, the primary objective of this study is to lay the groundwork for the pioneering spherical fuzzy Z-number model. This model showcases exceptional adeptness in articulating ambiguous information, thus serving as a valuable tool for informed decision-making amidst uncertainty. Notably, it not only enhances the precision of decision-making data but also embodies qualities of fuzziness, flexibility, and applicability, as evidenced in Table 1. Furthermore, this research introduces the PHI model, founded on fully developed Z-SF laws, and presents it through two distinct approaches: the PHI-based SF approach and the PHI-based Z-numbers approach. Finally, to validate the efficacy of the new model, the study applies it to identify critical barriers to adopting logistics supply chain management (SCM) simulation software within Vietnamese universities.

Table 1: Superiority of Z-SFSs over other fuzzy sets

Sets	$\boldsymbol{\alpha}$	$\boldsymbol{\beta}$	$\boldsymbol{\gamma}$	Reliability	Constraints
Fuzzy sets [1]	☑	O	O	O	$0 \leq \alpha \leq 1$
IFSs [2]	☑	☑	O	O	$0 \leq \alpha + \beta \leq 1$
PyFSs [26]	☑	☑	O	O	$0 \leq \alpha^2 + \beta^2 \leq 1$
qROFs [8]	☑	☑	O	O	$0 \leq \alpha^q + \beta^q \leq 1$
PFSs [11]	☑	☑	☑	O	$0 \leq \alpha + \beta + \gamma \leq 1$
SFSs [14]	☑	☑	☑	O	$0 \leq \alpha^2 + \beta^2 + \gamma^2 \leq 1$
Z-number [27]	☑	O	O	☑	$0 \leq \alpha\,(A, F) \leq 1$
This study (SFZs)	☑	☑	☑	☑	$0 \leq \alpha^2\,(A, F) \leq + \beta^2\,(A, F) \leq + \gamma^2\,(A, F) \leq 1$

Following this, this study's objective addresses two key questions: (RQ1) Does the new PHI method capture vague and uncertain information better than the previous group expert consensus techniques? (RQ2) Applying the new PHI method, what are the crucial barriers to adopting logistics SCM simulation software in universities in Vietnam?

This research pioneers the fully integrated use of Z-SF numbers within the Delphi approach by leveraging Z-numbers for information gathering and employing calculations based on SFSs. Initially, experts' assessments of criteria importance and evaluation reliability are collected simultaneously using a language scale. Subsequently, various aggregation approaches are applied to identify essential criteria influencing the research problem. Finally, correlations are employed to compare the PHI method based on the Spherical Fuzzy approach and the Z-SF Delphi method based on the Z-numbers approach with other techniques. The significant contributions of this study can be summarized as follows:

(i) This research introduces a novel method that surpasses previous Delphi approaches by integrating the advantages of SFSs and Z-numbers. Unlike prior methods [22,25], this new approach not only adeptly handles the ambiguity and uncertainty of information using SFSs but also accounts for the information's reliability level.

(ii) The proposed combined approach enhances established techniques, analytical precision, and decision-making abilities when investigating MCDM problems. Scholars and policymakers can utilize the two suggested approaches to the new method as a guide when applying them to various study areas, thus advancing the field's analytical capabilities and decision-making efficacy.

2 Preliminaries and Basic Theory

This section introduces several fundamental definitions and operations that played a crucial role in shaping the suggested work.

Definition 1 [1]: Suppose F is the universal set, then the fuzzy set is defined as:

$$\overline{X} = \{\langle f, \mu_{\overline{F}}(f)\rangle | f \in F\}$$

where $\mu_{\overline{F}}(f)$ is a membership degree of f in $\overline{X}$ and $\mu_{\overline{F}}: N \to [0,1]$.

Definition 2 [27]: A Z-number is an ordered pair of fuzzy numbers (A, R). The A component is the membership function, while R is the reliability of the A.

Definition 3 [22]: By applying the concept of fuzzy expected value, the Z-number can be converted to a fuzzy number:

$$E_A(f) = \int_F f \mu_{\overline{F}}(f)\, df \tag{1}$$

First, the Z-number (R) is transformed into a numerical value as the following geometrical:

$$\xi = \frac{\int f \mu_R(f)\, df}{\int \mu_R(f)\, df} \tag{2}$$

The computed weight ξ is added to the first component (A):

$$\overline{X}^{\xi} = \left\{ (f, \mu_{A^{\xi}}(f)), \mu_{A^{\xi}}(f) = \xi . \mu_A(f), f \in \sqrt{\xi} F \right\} \tag{3}$$

Then, the obtained fuzzy number $\overline{X}'$:

$$\overline{X}' = \left\{ (f, \mu_{\overline{X}'}(f)), \mu_{\overline{X}'}(f) = \left(\frac{f}{\sqrt{\xi}} \right) . \mu_{\overline{X}'}(f), f \in \sqrt{\xi} F \right\} \tag{4}$$

Definition 4 [14]: Let F be the universal set; the spherical fuzzy set is defined as follows:

$\overline{X} = \{\langle f, (\sigma(f), \varsigma(f), \tau(f))\rangle | f \in F\}$,

where $\sigma(f) \to [0,1]$, $\varsigma(f) \to [0,1]$, and $\tau(f) \to [0,1]$ be the degree of membership, non-membership, and hesitancy of f to $\overline{X}$ for each f, respectively, with the condition that $0 \leq \sigma^2(f) + \varsigma^2(f) + \tau^2(f) \leq 1$.

Definition 5 [21]: Let F be the universal set, then Spherical fuzzy Z-numbers are defined as the subsequent form:

$X_z = \{\langle f, (\sigma_{X_z}, \varsigma_{X_z}, \tau_{X_z}), (\varpi_{X_z}, \rho_{X_z}, \eta_{X_z})\rangle | f \in N\}$,

where $\sigma_{A_z}, \varsigma_{A_z}, \tau_{A_z}$ are the membership, non-membership, and hesitancy degrees of A component, while $\varpi_{A_z}, \rho_{A_z}, \eta_{A_z}$ are membership the membership, non-membership, and hesitancy degrees of R component; $\sigma_{A_z} \to [0,1]$, $\varsigma_{A_z} \to [0,1]$, and $\tau_{A_z} \to [0,1]$; and $\varpi_{X_z} \to [0,1]$, $\rho_{X_z \to [0,1]}$, and $\eta_{X_z} \to [0,1]$. And:

$0 \leq \sigma^2_{X_z} + \varsigma^2_{X_z} + \tau^2_{X_z} \leq 1$, and

$0 \leq \varpi^2_{X_z} + \rho^2_{X_z} + \tau^2_{X_z} \leq 1$

Definition 6 [21]: Suppose $X_z = ((\sigma_{X_z}, \varsigma_{X_z}, \tau_{X_z}), (\varpi_{X_z}, \rho_{X_z}, \eta_{X_z}))$ and $Y_z = ((\sigma_{Y_z}, \varsigma_{Y_z}, \tau_Y), (\varpi_{Y_z}, \rho_{Y_z}, \eta_{Y_z}))$ be two SFZNs and $\lambda > 0$. Then, by the following relations:

Union

$$X_z \cup Y_z = \left(\begin{array}{c} \left(\begin{array}{c} max(\sigma_{X_z}, \sigma_{Y_z}), min(\varsigma_{X_z}, \varsigma_{Y_z}), min\left(\sqrt{1 - max(\sigma_{X_z}, \sigma_{Y_z})^2 + min(\varsigma_{X_z}, \varsigma_{Y_z})^2} \right), \\ max(\tau_{X_z}, \tau_Y) \end{array} \right), \\ \left(\begin{array}{c} max(\varpi_{X_z}, \varpi_{Y_z}), min(\rho_{X_z}, \rho_{Y_z}), min\left(\sqrt{1 - max(\varpi_{X_z}, \varpi_{Y_z})^2 + min(\rho_{X_z}, \rho_{Y_z})^2} \right), \\ max(\eta_{X_z}, \eta_{Y_z}) \end{array} \right) \end{array} \right) \tag{5}$$

Intersection

$$X_z \cap Y_z = \left(\begin{array}{c} \left(\begin{array}{c} min(\sigma_{X_z}, \sigma_{Y_z}), max(\varsigma_{X_z}, \varsigma_{Y_z}), max\left(\sqrt{1 - min(\sigma_{X_z}, \sigma_{Y_z})^2 + max(\varsigma_{X_z}, \varsigma_{Y_z})^2} \right), \\ min(\tau_{X_z}, \tau_Y) \end{array} \right), \\ \left(\begin{array}{c} min(\varpi_{X_z}, \varpi_{Y_z}), max(\rho_{X_z}, \rho_{Y_z}), max\left(\sqrt{1 - min(\varpi_{X_z}, \varpi_{Y_z})^2 + max(\rho_{X_z}, \rho_{Y_z})^2} \right), \\ min(\eta_{X_z}, \eta_{Y_z}) \end{array} \right) \end{array} \right) \tag{6}$$

Addition

$$X_z \oplus Y_z = \left(\begin{array}{c} \left(\sqrt{(\sigma^2_{X_z} + \sigma^2_{Y_z} - \sigma^2_{X_z}.\sigma^2_{Y_z})}, \varsigma_{X_z}.\varsigma_{Y_z}, \sqrt{(1 - \sigma^2_{Y_z})\tau^2_{X_z} + ((1 - \sigma^2_{X_z})\tau^2_{Y_z}) - \tau^2_{X_z}.\tau^2_{Y_z}} \right), \\ \left(\sqrt{(\varpi^2_{X_z} + \varpi^2_{Y_z} - \varpi^2_{X_z}.\varpi^2_{Y_z})}, \rho_{X_z}.\rho_{Y_z}, \sqrt{(1 - \varpi^2_{Y_z})\eta^2_{X_z} + ((1 - \varpi^2_{X_z})\eta^2_{Y_z}) - \eta^2_{X_z}.\eta^2_{Y_z}} \right) \end{array} \right) \tag{7}$$

Multiplication

$$X_z \otimes Y_z = \left(\begin{array}{c} \left(\sigma_{X_z}.\sigma_{Y_z}, \sqrt{\varsigma_{X_z}^2 + \varsigma_{Y_z}^2 - \varsigma_{X_z}^2.\varsigma_{Y_z}^2}, \sqrt{\left(1-\varsigma_{Y_z}^2\right)\tau_{X_z}^2 + \left(1-\varsigma_{X_z}^2\right)\tau_{Y_z}^2 - \tau_{X_z}^2.\tau_{Y_z}^2} \right), \\ \left(\varpi_{X_z}.\varpi_{Y_z}, \sqrt{\rho_{X_z}^2 + \rho_{Y_z}^2 - \rho_{X_z}^2.\rho_{Y_z}^2}, \sqrt{\left(1-\rho_{Y_z}^2\right)\eta_{X_z}^2 + \left(1-\rho_{X_z}^2\right)\eta_{Y_z}^2 - \eta_{X_z}^2.\eta_{Y_z}^2} \right) \end{array} \right) \tag{8}$$

Multiplication by a scalar; $\lambda > 0$

$$\lambda \cdot X_z = \left(\begin{array}{c} \left(\sqrt{1-\left(1-\sigma_{X_z}^2\right)^{\lambda}}, \varsigma_{X_z}^{\lambda}, \sqrt{\left(1-\sigma_{X_z}^2\right)^{\lambda} - \left(1-\sigma_{X_z}^2 - \tau_{X_z}^2\right)^{\lambda}} \right), \\ \left(\sqrt{1-\left(1-\varpi_{X_z}^2\right)^{\lambda}}, \rho_{X_z}^{\lambda}, \sqrt{\left(1-\varpi_{X_z}^2\right)^{\lambda} - \left(1-\varpi_{X_z}^2 - \eta_{X_z}^2\right)^{\lambda}} \right) \end{array} \right) \tag{9}$$

Power of $X_z; \lambda > 0$

$$X_z^{\lambda} = \left(\begin{array}{c} \left(\sigma_{X_z}^{\lambda}, \sqrt{1-\left(1-\varsigma_{X_z}^2\right)^{\lambda}}, \sqrt{\left(1-\varsigma_{X_z}^2\right)^{\lambda} - \left(1-\varsigma_{X_z}^2 - \tau_{X_z}^2\right)^{\lambda}} \right), \\ \left(\varpi_{X_z}^{\lambda}, \sqrt{1-\left(1-\rho_{X_z}^2\right)^{\lambda}}, \sqrt{\left(1-\rho_{X_z}^2\right)^{\lambda} - \left(1-\rho_{X_z}^2 - \eta_{X_z}^2\right)^{\lambda}} \right) \end{array} \right) \tag{10}$$

Definition 7 [21]: Spherical fuzzy Z-number weighted arithmetic (SFZNWA) with respect to $\lambda = (\lambda_1, \lambda_2, \ldots, \lambda_n); \lambda_i \in [0,1]; \sum_{i=1}^{n} \lambda_i = 1$, SFZNWA is defined as:

$$SFZNWA_{\lambda}\left(X_{z_1}, \ldots, X_{z_n}\right) = \sum_{i=1}^{n} \lambda_1.X_{z_i} = \lambda_1.X_{z_1} + \lambda_2.X_{z_2} + \ldots + \lambda_n.X_{z_n} \tag{11}$$

$$= \left(\left(\begin{array}{c} \sqrt{1-\prod_{i=1}^{n}\left(1-\sigma_{X_{z_i}}^2\right)^{\lambda_i}}, \prod_{i=1}^{n} \varsigma_{X_{z_i}}^{\lambda_i}, \\ \sqrt{\prod_{i=1}^{n}\left(1-\sigma_{X_{z_i}}^2\right)^{\lambda_i} - \prod_{i=1}^{n}\left(1-\sigma_{X_{z_i}}^2 - \tau_{X_{z_i}}^2\right)^{\lambda_i}} \end{array} \right), \left(\begin{array}{c} \sqrt{1-\prod_{i=1}^{n}\left(1-\varpi_{X_{z_i}}^2\right)^{\lambda_i}}, \prod_{i=1}^{n} \rho_{X_{z_i}}^{\lambda_i}, \\ \sqrt{\prod_{i=1}^{n}\left(1-\varpi_{X_{z_i}}^2\right)^{\lambda_i} - \prod_{i=1}^{n}\left(1-\varpi_{X_{z_i}}^2 - \eta_{X_{z_i}}^2\right)^{\lambda_i}} \end{array} \right) \right)$$

Definition 8 [21]: Spherical fuzzy Z-number weighted geometric (SFZNWG) with respect to $\lambda = (\lambda_1, \lambda_2, \ldots, \lambda_n); \lambda_i \in [0,1]; \sum_{i=1}^{n} \lambda_i = 1$, SFZNWG is defined as:

$$SFZNWG_{\lambda}\left(X_{z_1}, \ldots, X_{z_n}\right) = \prod_{i=1}^{n} X_{z_i}^{\lambda_i} = X_{z_1}^{\lambda_1} \cdot X_{z_2}^{\lambda_2} \cdot \ldots \cdot X_{z_i}^{\lambda_i} \tag{12}$$

$$= \left(\left(\begin{array}{c} \prod_{i=1}^{n} \sigma_{X_{z_i}}^{\lambda_i}, \sqrt{1-\prod_{i=1}^{n}\left(1-\varsigma_{X_{z_i}}^2\right)^{\lambda_i}}, \\ \sqrt{\prod_{i=1}^{n}\left(1-\varsigma_{X_{z_i}}^2\right)^{\lambda_i} - \prod_{i=1}^{n}\left(1-\varsigma_{X_{z_i}}^2 - \tau_{X_{z_i}}^2\right)^{\lambda_i}} \end{array} \right), \left(\begin{array}{c} \prod_{i=1}^{n} \varpi_{X_{z_i}}^{\lambda_i}, \sqrt{1-\prod_{i=1}^{n}\left(1-\rho_{X_{z_i}}^2\right)^{\lambda_i}}, \\ \sqrt{\prod_{i=1}^{n}\left(1-\rho_{X_{z_i}}^2\right)^{\lambda_i} - \prod_{i=1}^{n}\left(1-\rho_{X_{z_i}}^2 - \eta_{X_{z_i}}^2\right)^{\lambda_i}} \end{array} \right) \right)$$

Definition 9 [14]: SFZNs are transformed into Spherical fuzzy numbers X_F:

$$X_F = \left(\left(\sigma_{X_z}, \varsigma_{X_z}, \tau_{X_z}\right) \otimes \left(\varpi_{X_z}, \rho_{X_z}, \eta_{X_z}\right)\right)$$

$$= \left(\sigma_{X_z}.\varpi_{X_z}, \sqrt{\varsigma_{X_z}^2 + \rho_{X_z}^2 - \varsigma_{X_z}^2.\rho_{X_z}^2}, \sqrt{\left(1-\rho_{X_z}^2\right)\tau_{X_{z_i}}^2 + \left(1-\varsigma_{X_{z_i}}^2\right)\eta_{X_{z_i}}^2 - \tau_{X_{z_i}}^2.\eta_{X_{z_i}}^2} \right) \tag{13}$$

3 Proposed Model of PHI Model-Based SFZNs

3.1 PHI-Based SFSs Approach

The expert's evaluations can be displayed as Z-numbers, indicating the boundary's certainty and value for the required problem. With the combination of SFZNs, the author gathered the experts' views of the concerned topic and the reliability level of their rate using the linguistic scales in Tables 2 and 3.

Table 2: The linguistic scale for restriction components

Linguistic terms	Code	$\left(\sigma_{X_z}, \varsigma_{X_z}, \tau_{X_z}\right)$
Absolutely more importance	AMI	(0.9, 0.1, 0.1)
Very high importance	VHI	(0.8, 0.2, 0.2)
High importance	HI	(0.7, 0.3, 0.3)
Slightly more important	SMI	(0.6, 0.4, 0.4)
Equally important	EI	(0.5, 0.5, 0.5)
Slightly low importance	SLI	(0.4, 0.6, 0.4)
Low importance	LI	(0.3, 0.7, 0.3)
Very low importance	VLI	(0.2, 0.8, 0.2)
Absolutely low importance	ALI	(0.1, 0.9, 0.1)

Table 3: The linguistic scale for reliability components

Linguistic terms	Code	$\left(\varpi_{X_z}, \rho_{X_z}, \eta_{X_z}\right)$
Very sure	VS	(0.9, 0.1, 0)
Sure	SU	(0.8, 0.2, 0.1)
Possible	PO	(0.7, 0.3, 0.2)
Uncertain	UN	(0.6, 0.4, 0.3)

Step 1: Experts $E_i = (1, 2, \ldots, n)$ declare their evaluations, giving SFZ numbers using Eq. (14):

$$X_{z_i} = \left(\left(\sigma_{X_{z_i}}, \varsigma_{X_{z_i}}, \tau_{X_{z_i}}\right), \left(\varpi_{X_{z_i}}, \rho_{X_{z_i}}, \eta_{X_{z_i}}\right)\right) \tag{14}$$

where the $\left(\sigma_{X_z}, \varsigma_{X_z}, \tau_{X_z}\right)$ component is the rank of the criteria using the linguistic terms listed in Table 2, while $\left(\varpi_{X_z}, \rho_{X_z}, \eta_{X_z}\right)$ component is the level of reliability using the linguistic terms listed in Table 3.

Step 2: The SFZNWA Eq. (11) or SFZNWG operator Eq. (12) is used to obtain the significance level of each indicator, which is displayed in Eq. (15):

$$U_z^{agg} = \begin{bmatrix} \left(\left(\sigma_{X_{z_{11}}}, \varsigma_{X_{z_{11}}}, \tau_{X_{z_{11}}}\right), \left(\varpi_{X_{z_{11}}}, \rho_{X_{z_{11}}}, \eta_{X_{z_{11}}}\right)\right) & \cdots & \left(\left(\sigma_{X_{z_{1m}}}, \varsigma_{X_{z_{1m}}}, \tau_{X_{z_{1m}}}\right), \left(\varpi_{X_{z_{1m}}}, \rho_{X_{z_{1m}}}, \eta_{X_{z_{1m}}}\right)\right) \\ \vdots & \vdots & \vdots \\ \left(\left(\sigma_{X_{z_{n1}}}, \varsigma_{X_{z_{n1}}}, \tau_{X_{z_{n1}}}\right), \left(\varpi_{X_{z_{n1}}}, \rho_{X_{z_{n1}}}, \eta_{X_{z_{n1}}}\right)\right) & \cdots & \left(\left(\sigma_{X_{z_{nm}}}, \varsigma_{X_{z_{nm}}}, \tau_{X_{z_{nm}}}\right), \left(\varpi_{X_{z_{nm}}}, \rho_{X_{z_{nm}}}, \eta_{X_{z_{nm}}}\right)\right) \end{bmatrix} \tag{15}$$

Step 3: Transform SFZNs into SFSs numbers using Eqs. (13) and (16).

$$U_S^{agg} = \begin{bmatrix} (\mu_{11}, \nu_{11}, \pi_{11}) & \cdots & (\mu_{1m}, \nu_{1m}, \pi_{1m}) \\ \vdots & \ddots & \vdots \\ (\mu_{n1}, \nu_{n1}, \pi_{n1}) & \cdots & (\mu_{nm}, \nu_{nm}, \pi_{nm}) \end{bmatrix} \tag{16}$$

Step 4: Transforming SFSs numbers into crisp numbers by using Eq. (17):

$$\text{Score}\,(d_i) = \left(2\mu_{ij} - \pi_{ij}\right)^2 - \left(\nu_{ij} - \pi_{ij}\right)^2 \tag{17}$$

Step 5: Calculate the threshold by Eq. (18) and validate the criteria.

$$D = \sum_{i=1}^{n} \frac{d_i}{m} \tag{18}$$

If $d_i < D$, criterion C_i is removed, and if $d_i > D$, criterion C_i is valid.

3.2 PHI-Based Z-Number Approach

Step 1: This step is the same as Step 1 of the PHI-Based SFSs Approach.

Step 2: The Z-numbers are converted into SFSs numbers by Eqs. (2)–(4). The resulting fuzzy numbers take the following form:

$$\overline{X'}_{z_i} = \left(\mu_{\overline{X'}_{z_i}}, \nu_{\overline{X'}_{z_i}}, \pi_{\overline{X'}_{z_i}}\right) \tag{19}$$

Step 3: Eq. (16) presents the SFZ decision matrix.

Step 4: The utilization of either the SFZNWA Eq. (11) or the SFZNWG operator Eq. (12) is applied to determine the significance level of the criterion, as illustrated in Eq. (20):

$$U_S^{agg} = \begin{bmatrix} \left(\mu_{11}^{agg}, \nu_{11}^{agg}, \pi_{11}^{agg}\right) & \cdots & \left(\mu_{1m}^{agg}, \mu_{1m}^{agg}, \mu_{1m}^{agg}\right) \\ \vdots & \ddots & \vdots \\ \left(\mu_{n1}^{agg}, \nu_{n1}^{agg}, \pi_{n1}^{agg}\right) & \cdots & \left(\mu_{nm}^{agg}, \mu_{nm}^{agg}, \mu_{nm}^{agg}\right) \end{bmatrix} \tag{20}$$

Step 5: Transforming Spherical fuzzy numbers into crisp numbers by using Eq. (17).

Step 6: Calculate the threshold by Eq. (18) and validate the criteria. If $d_i < D$, criterion C_i is removed, and if $d_i > D$, criterion C_i is valid.

4 Case Study

Adopting logistics Supply Chain Management (SCM) simulation software in Vietnamese universities has encountered various barriers, hindering its widespread implementation. Many universities in Vietnam may not fully comprehend how these software solutions can enhance the learning experience for students in logistics and supply chain management programs. Financial constraints pose a significant challenge, as investing in advanced simulation software requires a substantial upfront cost. Moreover, there is a shortage of skilled professionals who can effectively integrate and utilize SCM simulation software in educational settings. Overcoming these barriers will necessitate targeted efforts to raise awareness, secure funding, and provide adequate training to educators, thereby fostering a conducive environment for integrating logistics SCM simulation software in Vietnamese universities.

Through a comprehensive literature review, Table 4 highlights various challenges organizations face when trying to adopt simulation software, such as EPR (Enterprise Resource Planning) or logistics Supply Chain Management.

Table 4: Barriers related to the adoption of logistics scm simulation platforms

Code	Barriers	Code	Barriers
C1	High upfront costs	C11	Limited computational power
C2	Lack of expertise	C12	Lack of industry-specific templates
C3	Integration challenges	C13	Inability to adapt to business changes
C4	Cultural resistance	C14	Opportunity cost
C5	Complexity	C15	Uncertain ROI
C6	Integration challenges with analytics tools	C16	Lack of trust
C7	Data security concerns	C17	Resistance to change
C8	Theoretical results	C18	Vendor expertise mismatch
C9	Long sales cycles	C19	Customization complexity
C10	Implementation time	C20	Automation concerns

4.1 Demographic of Experts

A questionnaire comprising 20 barriers associated with adopting the logistic SCM simulation platform was distributed to 13 experts within the educational domain. Responses were received from 10 experts, and Table 5 provides an overview of their demographics.

Table 5: Experts' demographic information

EP's information	EP1	EP2	EP3	EP4	EP5
Years of experience	15	14	10	12	12
Education level	Doctor	Master	Master	Master	Master
Positions	Policymaker	Lecturer	University administrator	Lecturer	Lecturer
Linguistic evaluation	AMI	HI	EI	SMI	HI
EP's weights	0.114	0.104	0.086	0.096	0.104
EP's information	**EP6**	**EP7**	**EP8**	**EP9**	**EP10**
Years of experience	18	15	11	12	11
Education level	Doctor	Doctor	Doctor	Master	Master
Positions	Lecturer	Lecturer	University administrator	University administrator	Policymaker
Linguistic evaluation	AMI	HI	EI	HI	EI
EP's weights	0.114	0.104	0.086	0.104	0.086

Based on the information provided in Table 5, it can be affirmed that the selected experts possess diverse experiences, educational backgrounds, and professional positions within the educational domain. This diversity contributes to a well-rounded and comprehensive evaluation of the barriers to adopting the logistic SCM simulation platform. The linguistic evaluations and weights assigned by each expert further underscore the suitability of this expert panel in offering valuable insights for this study.

4.1.1 *Results of PHI-Based SFSs Approach*

After collecting experts' evaluations, the author transforms this information into SFZNs numbers based on Tables 2 and 3. The SFZNWA–Eqs. (11) and (15) are used to obtain the significance vector for each barrier. The SFZN significance vectors are transformed into SFSs numbers by Eq. (16), and SFSs numbers are continually transformed into crisp numbers using Eq. (17). Finally, the threshold is calculated by Eq. (18) to validate the barriers. The results are displayed in Table 6. Similarly, the SFZNWG results are shown in Table 7.

Table 6: Results of PHI-based SFSs approach with SFZNWA

Barriers	SFZNWA		SF numbers	Crisp numbers	Valid	Rank
	$(\sigma, \varsigma, \tau)$	(ϖ, ρ, η)	(μ, ν, π)			
C1	(0.774, 0.232, 0.255)	(0.878, 0.122, 0.043)	(0.68, 0.26, 0.256)	1.217	Consent	10
C2	(0.626, 0.389, 0.366)	(0.884, 0.116, 0.037)	(0.553, 0.403, 0.365)	0.548	Reject	17
C3	(0.758, 0.247, 0.266)	(0.886, 0.115, 0.035)	(0.671, 0.271, 0.266)	1.158	Consent	14
C4	(0.6, 0.412, 0.356)	(0.876, 0.124, 0.045)	(0.526, 0.427, 0.355)	0.480	Reject	19
C5	(0.767, 0.239, 0.265)	(0.886, 0.114, 0.034)	(0.68, 0.264, 0.265)	1.199	Consent	12
C6	(0.613, 0.394, 0.39)	(0.87, 0.13, 0.051)	(0.533, 0.412, 0.389)	0.459	Reject	20
C7	(0.806, 0.197, 0.214)	(0.848, 0.152, 0.069)	(0.684, 0.247, 0.222)	1.314	Consent	6
C8	(0.805, 0.199, 0.221)	(0.851, 0.15, 0.067)	(0.685, 0.247, 0.227)	1.305	Consent	7
C9	(0.797, 0.208, 0.228)	(0.839, 0.162, 0.076)	(0.668, 0.261, 0.236)	1.210	Consent	11
C10	(0.787, 0.215, 0.227)	(0.84, 0.161, 0.075)	(0.661, 0.267, 0.235)	1.182	Consent	13
C11	(0.773, 0.229, 0.236)	(0.85, 0.151, 0.068)	(0.657, 0.272, 0.242)	1.149	Consent	15
C12	(0.817, 0.188, 0.212)	(0.858, 0.143, 0.062)	(0.701, 0.234, 0.218)	1.400	Consent	2
C13	(0.787, 0.22, 0.251)	(0.885, 0.116, 0.036)	(0.696, 0.247, 0.251)	1.301	Consent	8
C14	(0.799, 0.205, 0.225)	(0.87, 0.13, 0.051)	(0.696, 0.241, 0.228)	1.354	Consent	5
C15	(0.805, 0.199, 0.216)	(0.842, 0.159, 0.074)	(0.677, 0.253, 0.224)	1.277	Consent	9
C16	(0.82, 0.184, 0.211)	(0.849, 0.151, 0.068)	(0.697, 0.237, 0.218)	1.380	Consent	3
C17	(0.809, 0.196, 0.218)	(0.86, 0.141, 0.06)	(0.695, 0.24, 0.224)	1.362	Consent	4
C18	(0.704, 0.305, 0.313)	(0.851, 0.15, 0.067)	(0.6, 0.336, 0.315)	0.782	Reject	16
C19	(0.825, 0.18, 0.208)	(0.849, 0.151, 0.068)	(0.701, 0.233, 0.216)	1.406	Consent	1
C20	(0.66, 0.354, 0.342)	(0.812, 0.188, 0.093)	(0.536, 0.395, 0.345)	0.524	Reject	18
Threshold				**1.100**		

Table 7: Results of PHI-based SFSs approach with SFZNWG

Barriers	SFZNWG		SF numbers	Crisp numbers	Valid	Rank
	$(\sigma, \varsigma, \tau)$	(ϖ, ρ, η)	(μ, ν, π)			
C1	(0.726, 0.296, 0.31)	(0.87, 0.137, 0.054)	(0.631, 0.324, 0.311)	0.906	Consent	13
C2	(0.552, 0.466, 0.408)	(0.877, 0.129, 0.047)	(0.485, 0.48, 0.406)	0.311	Reject	18
C3	(0.718, 0.298, 0.31)	(0.879, 0.127, 0.045)	(0.631, 0.322, 0.311)	0.906	Consent	12
C4	(0.543, 0.472, 0.377)	(0.867, 0.14, 0.057)	(0.471, 0.488, 0.376)	0.307	Reject	20
C5	(0.713, 0.307, 0.315)	(0.88, 0.126, 0.044)	(0.627, 0.33, 0.315)	0.882	Consent	15
C6	(0.581, 0.429, 0.412)	(0.86, 0.147, 0.062)	(0.5, 0.449, 0.41)	0.345	Reject	17
C7	(0.771, 0.246, 0.253)	(0.838, 0.168, 0.079)	(0.646, 0.296, 0.26)	1.066	Consent	1
C8	(0.762, 0.262, 0.277)	(0.84, 0.166, 0.077)	(0.64, 0.307, 0.282)	0.996	Consent	9
C9	(0.755, 0.264, 0.271)	(0.829, 0.176, 0.084)	(0.626, 0.314, 0.278)	0.948	Consent	11
C10	(0.764, 0.246, 0.249)	(0.83, 0.175, 0.083)	(0.634, 0.299, 0.257)	1.020	Consent	7
C11	(0.757, 0.25, 0.252)	(0.839, 0.167, 0.077)	(0.636, 0.297, 0.258)	1.025	Consent	6
C12	(0.767, 0.262, 0.279)	(0.847, 0.16, 0.072)	(0.65, 0.304, 0.283)	1.033	Consent	5
C13	(0.723, 0.305, 0.323)	(0.878, 0.128, 0.046)	(0.635, 0.329, 0.323)	0.898	Consent	14
C14	(0.758, 0.262, 0.27)	(0.86, 0.147, 0.062)	(0.653, 0.298, 0.273)	1.064	Consent	2
C15	(0.769, 0.248, 0.253)	(0.832, 0.174, 0.082)	(0.64, 0.299, 0.261)	1.038	Consent	4
C16	(0.768, 0.264, 0.284)	(0.839, 0.168, 0.078)	(0.644, 0.31, 0.289)	0.997	Consent	8
C17	(0.762, 0.261, 0.269)	(0.849, 0.158, 0.071)	(0.647, 0.302, 0.274)	1.039	Consent	3
C18	(0.642, 0.379, 0.361)	(0.84, 0.166, 0.077)	(0.54, 0.409, 0.362)	0.513	Reject	16
C19	(0.767, 0.266, 0.285)	(0.839, 0.168, 0.078)	(0.643, 0.311, 0.29)	0.993	Consent	10
C20	(0.585, 0.434, 0.382)	(0.808, 0.194, 0.096)	(0.473, 0.468, 0.383)	0.310	Reject	19
Threshold				**0.830**		

The Spearman correlation (Eq. (21)) is applied to investigate the relationship between two operators, SFZNWA and SFZNWG, $r_s = 0.727$ (higher than 0.7). Therefore, the ranking results of SFZN-Delphi Using the SFs Approach by two operators have a high level of consistency. Furthermore, according to Tables 5 and 6, both SFZN-Delphi of SFZNWA and SFZNWG indicated that there are 15 barriers appropriate to the research scope, and five are eliminated. Specifically, the barriers C2, C4, C6, C18, and C20 were not suitable for adopting SCM simulation platforms for logistics in universities in the context of Vietnam.

$$r_s = 1 - \frac{6 \sum \left(R_{xi} - R_{yi}\right)^2}{n\left(n^2 - 1\right)} \tag{21}$$

4.1.2 Results of PHI-Based Z-Numbers Approach

Unlike SFZN-Delphi, using the SFs approach, the reliability components were presented through Eq. (19) after collecting expert evaluation. Then, the author took the square of ξ to multiply with restriction components by Eq. (16). Then, the SFZNWA (Eq. (11)), SFZNWG operator (Eq. (12)), and Eq. (20) obtain the significance vector for each barrier. The results are shown in Tables 8 and 9.

Like SFZN-Delphi Using SFs Approach, The Spherical fuzzy numbers are transformed into crisp numbers using Eq. (17). Finally, the threshold is calculated by Eq. (18) to validate the barriers.

Table 8: The results of ξ

Linguistic terms	Code	$(\boldsymbol{\varpi}, \boldsymbol{\rho}, \boldsymbol{\eta})$	$\boldsymbol{\xi}$
Very sure	VS	(0.9, 0.1, 0.1)	0.333
Sure	SU	(0.8, 0.2, 0.2)	0.367
Possible	PO	(0.7, 0.3, 0.3)	0.400
Uncertain	UN	(0.6, 0.4, 0.4)	0.433

Table 9: Results of PHI-based Z-numbers approach

Barriers	SWAM	Crisp numbers	Valid	Rank	SWGM	Crisp numbers	Valid	Rank
	(μ, ν, π)				(μ, ν, π)			
C1	(0.644, 0.424, 0.239)	1.067	Consent	13	(0.602, 0.474, 0.282)	0.812	Consent	12
C2	(0.501, 0.577, 0.319)	0.400	Reject	18	(0.442, 0.628, 0.351)	0.208	Reject	19
C3	(0.627, 0.442, 0.247)	0.977	Reject	15	(0.592, 0.481, 0.281)	0.775	Reject	14
C4	(0.481, 0.593, 0.305)	0.348	Reject	20	(0.434, 0.634, 0.321)	0.200	Reject	20
C5	(0.635, 0.436, 0.249)	1.006	Reject	14	(0.589, 0.486, 0.284)	0.757	Reject	15
C6	(0.491, 0.578, 0.339)	0.358	Reject	19	(0.466, 0.601, 0.356)	0.271	Reject	18
C7	(0.68, 0.382, 0.208)	1.297	Consent	5	(0.651, 0.418, 0.235)	1.103	Consent	1
C8	(0.679, 0.384, 0.213)	1.282	Consent	7	(0.641, 0.431, 0.257)	1.023	Consent	9
C9	(0.673, 0.39, 0.218)	1.243	Consent	8	(0.635, 0.437, 0.25)	1.006	Consent	11
C10	(0.662, 0.4, 0.216)	1.193	Consent	10	(0.641, 0.425, 0.231)	1.067	Consent	3
C11	(0.647, 0.416, 0.222)	1.111	Consent	12	(0.632, 0.433, 0.233)	1.024	Consent	8
C12	(0.691, 0.372, 0.208)	1.353	Consent	3	(0.648, 0.427, 0.259)	1.046	Consent	6
C13	(0.657, 0.413, 0.238)	1.128	Consent	11	(0.601, 0.479, 0.293)	0.791	Reject	13
C14	(0.671, 0.394, 0.216)	1.235	Consent	9	(0.635, 0.437, 0.249)	1.009	Consent	10
C15	(0.679, 0.383, 0.209)	1.291	Consent	6	(0.649, 0.42, 0.236)	1.096	Consent	2
C16	(0.696, 0.366, 0.206)	1.382	Consent	2	(0.65, 0.427, 0.264)	1.046	Consent	5
C17	(0.683, 0.381, 0.212)	1.303	Consent	4	(0.641, 0.433, 0.249)	1.035	Consent	7
C18	(0.577, 0.495, 0.284)	0.715	Reject	16	(0.526, 0.547, 0.32)	0.485	Reject	16
C19	(0.702, 0.361, 0.206)	1.412	Consent	1	(0.65, 0.427, 0.264)	1.046	Consent	4
C20	(0.54, 0.534, 0.303)	0.551	Reject	17	(0.478, 0.592, 0.334)	0.320	Reject	17
Threshold		**1.032**				**0.806**		

The Spearman correlation in Eq. (21) is applied to investigate the relationship between two operators, SFZNWA and SFZNWG, $r_s = 0.883$ (higher than 0.7). Therefore, the ranking results of SFZN-Delphi Using the Z-Numbers Approach by two operators have a high level of consistency. However, based on Table 9, the results of the SFZN-Delphi-Based Z-Numbers Approach by the two operators are slightly different. There are seven barriers eliminated by the SFZNWA operator (C2, C3, C4, C5, C6, C18 and C20) and eight barriers eliminated by the SFZNWG operator (C2, C3, C4, C5, C6, C13, C18 and C20).

4.2 Comparative Analysis

To investigate the appropriateness of the newly proposed methods, the author used three spherical Z-number approaches proposed by Alkan et al. [28] to assess the relationships between various Delphi techniques.

4.2.1 The First Is Named SFZN-Delphi, and It Has Defuzzified Restriction and Reliability Functions

First, after collecting expert evaluations, we defuzzify the reliability components in each pairwise comparison matrix using Eq. (22) and normalize the obtained values using Eq. (23). Then, we multiply the SF restriction values in each pairwise comparison matrix by the square root of the normalized reliability values using Eq. (24). Third, Eqs. (11) or (12) is used to aggregate the values in pairwise comparison matrices obtained in the previous step. Finally, the score function is found using Eq. (22) and compared with the threshold by Eq. (18) to validate the criteria.

$$S\left(\tilde{w}_j^s\right) = \sqrt{\left|100 \cdot \left[\left(3\mu_{\tilde{A}_s} - \frac{\pi_{\tilde{A}_s}}{2}\right)^2 - \left(\frac{\vartheta_{\tilde{A}_s}}{2} - \pi_{\tilde{A}_s}\right)^2\right]\right|} \tag{22}$$

$$\tilde{w}_j^s = \frac{S\left(\tilde{w}_j^s\right)}{\sum_{j=1}^{n} S\left(\tilde{w}_j^s\right)} \tag{23}$$

$$k\tilde{A}_s = \left(\sqrt{1 - \left(1 - \mu_{\tilde{A}_s}^2\right)^k}, \vartheta_{\tilde{A}_s}^k, \sqrt{\left(1 - \mu_{\tilde{A}_s}^2\right)^k - \left(1 - \mu_{\tilde{A}_s}^2 - \pi_{\tilde{A}_s}^2\right)^k}\right) \tag{24}$$

4.2.2 The Second Was Named SFZN-Delphi with Aggregated and Defuzzified Reliability Function

First, the components in each pairwise comparison matrix are aggregated and defuzzified using Eqs. (11) or (12) and (22), respectively, and normalize the obtained values using Eq. (23). Secondly, we multiply the aggregated restriction vector by the square root of the normalized reliability values using Eq. (24). Finally, the score function is found using Eq. (22) and compared with the threshold by Eq. (18) to validate the criteria.

4.2.3 The Third Is Named Fully Completed PHI-Based SFZNs Models

Firstly, we compute the square root of each SF number in the reliability matrix. Then, we multiply the SF restriction values in pairwise comparison matrices by the values obtained before using Eq. (25). Similarly to the previous methods, the score function is found using Eq. (22) and compared with the threshold using Eq. (18) to validate the criteria.

$$\widetilde{A}_s \otimes \widetilde{B}_s = \left(\mu_{\tilde{A}_s}, \mu_{\tilde{B}_s}, \sqrt{\vartheta_{\tilde{A}_s}^2 + \vartheta_{\tilde{B}_s}^2 - \vartheta_{\tilde{A}_s}^2 \vartheta_{\tilde{B}_s}^2}, \sqrt{\left(1 - \vartheta_{\tilde{B}_s}^2\right)\pi_{\tilde{A}_s}^2 + \left(1 - \vartheta_{\tilde{A}_s}^2\right)\pi_{\tilde{B}_s}^2 - \pi_{\tilde{A}_s}^2 \pi_{\tilde{B}_s}^2}\right) \tag{25}$$

The results of the three approaches for using SWAM and SWGM operators are presented in Tables 10 and 11, respectively. The results show that, from the perspective of the SWAM operator, the first and second approaches have 14 appropriate and six inappropriate barriers (C2, C3, C4, C6, C18 and C20). The third approach has 15 appropriate and five unacceptable barriers (C2, C4, C6, C18, and C20). The results of the third approach are consistent with those of the SFZN-Delphi approach. In SWGM, the three approaches have 15 appropriate and five inappropriate barriers (C2, C4, C6, C18, and C20).

Table 10: Results of three approaches by using the SWAM operator

Barriers	The first approach			The second approach			The third approach		
	Crisp	Valid	Rank	Crisp	Valid	Rank	Crisp	Valid	Rank
C1	13.932	Consent	12	11.894	Consent	12	20.692	Consent	11
C2	10.112	Reject	18	8.457	Reject	18	16.652	Reject	17
C3	13.490	Reject	15	11.502	Reject	15	20.443	Consent	14
C4	9.542	Reject	20	7.974	Reject	20	15.638	Reject	20
C5	13.851	Consent	14	11.724	Consent	14	20.845	Consent	10
C6	9.728	Reject	19	8.147	Reject	19	16.009	Reject	19
C7	14.934	Consent	5	12.784	Consent	5	21.346	Consent	6
C8	14.821	Consent	7	12.724	Consent	6	21.207	Consent	7
C9	14.464	Consent	9	12.472	Consent	9	20.519	Consent	13
C10	14.269	Consent	11	12.240	Consent	10	20.543	Consent	12
C11	13.873	Consent	13	11.884	Consent	13	20.276	Consent	15
C12	15.244	Consent	3	13.086	Consent	3	21.664	Consent	2
C13	14.326	Consent	10	12.235	Consent	11	21.166	Consent	8
C14	14.771	Consent	8	12.610	Consent	8	21.495	Consent	4
C15	14.833	Consent	6	12.719	Consent	7	21.134	Consent	9
C16	15.287	Consent	2	13.164	Consent	2	21.566	Consent	3
C17	14.984	Consent	4	12.858	Consent	4	21.404	Consent	5
C18	11.964	Reject	16	10.132	Reject	16	18.295	Reject	16
C19	15.457	Consent	1	13.314	Consent	1	21.668	Consent	1
C20	10.667	Reject	17	9.077	Reject	17	16.111	Reject	18
Threshold	**13.527**			**11.550**			**19.934**		

Table 11: Results of three approaches by using the SWGM operator

Barriers	The first approach			The second approach			The third approach		
	Crisp	Valid	Rank	Crisp	Valid	Rank	Crisp	Valid	Rank
C1	12.832	Consent	13	10.637	Consent	12	19.591	Consent	13
C2	8.600	Reject	19	7.003	Reject	19	14.573	Reject	18
C3	12.580	Consent	14	10.486	Consent	14	19.520	Consent	14
C4	8.450	Reject	20	6.864	Reject	20	14.182	Reject	20
C5	12.542	Consent	15	10.355	Consent	15	19.253	Consent	15
C6	9.062	Reject	18	7.501	Reject	18	15.097	Reject	17
C7	14.023	Consent	1	11.784	Consent	1	20.209	Consent	3
C8	13.753	Consent	7	11.494	Consent	8	20.069	Consent	8
C9	13.538	Consent	10	11.341	Consent	11	19.705	Consent	11
C10	13.708	Consent	9	11.600	Consent	5	19.924	Consent	9

(Continued)

Table 11 (continued)

Barriers	The first approach			The second approach			The third approach		
	Crisp	Valid	Rank	Crisp	Valid	Rank	Crisp	Valid	Rank
C11	13.523	Consent	11	11.460	Consent	10	19.920	Consent	10
C12	13.978	Consent	3	11.619	Consent	3	20.257	Consent	2
C13	12.854	Consent	12	10.561	Consent	13	19.683	Consent	12
C14	13.751	Consent	8	11.468	Consent	9	20.302	Consent	1
C15	13.942	Consent	5	11.727	Consent	2	20.079	Consent	7
C16	13.970	Consent	4	11.607	Consent	4	20.208	Consent	4
C17	13.849	Consent	6	11.531	Consent	7	20.198	Consent	5
C18	10.589	Reject	16	8.746	Reject	16	16.555	Reject	16
C19	13.994	Consent	2	11.588	Consent	6	20.130	Consent	6
C20	9.190	Reject	17	7.569	Reject	17	14.432	Reject	19
Threshold	**12.436**			**10.347**			**18.694**		

Figs. 1 and 2 compare the results obtained using these three methods. The comparison reveals that the value of the crisp numbers of these barriers is similar across the approaches. However, there are some slight differences in the ranking of these barriers. Specifically, the ranking of the SWAM operator is more stable than that of the SWGM operator.

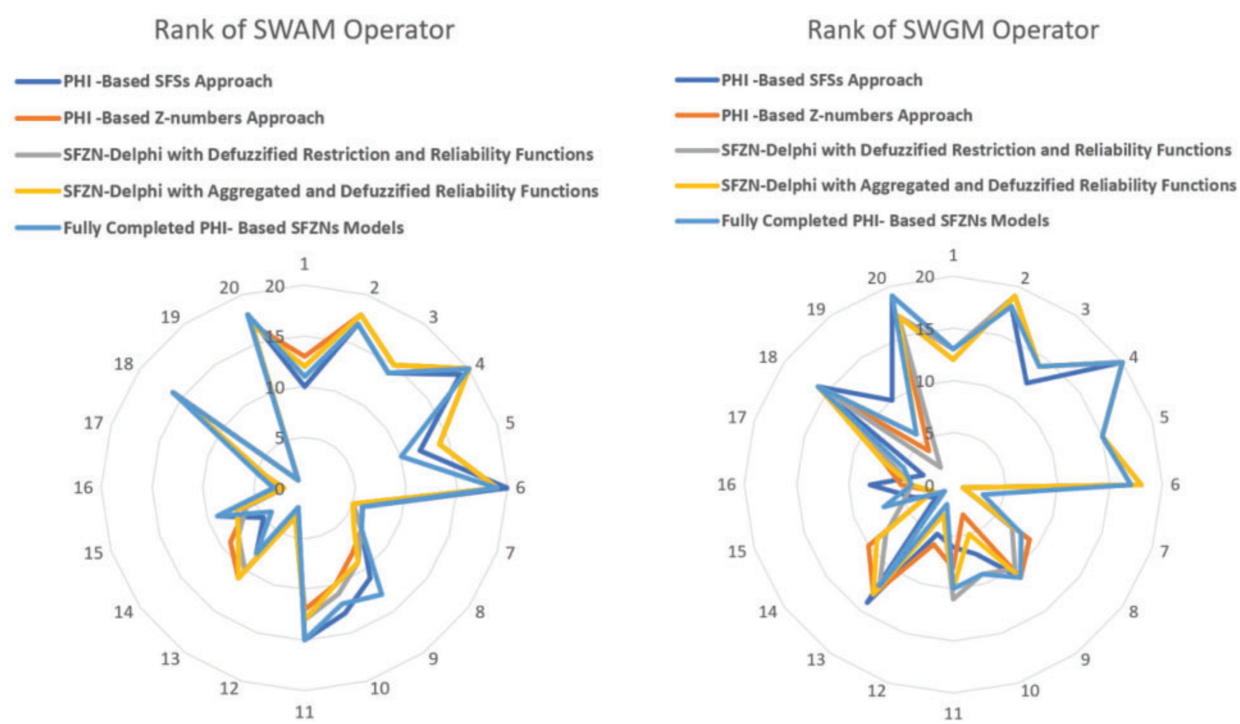

Figure 1: Comparative analysis based on rank

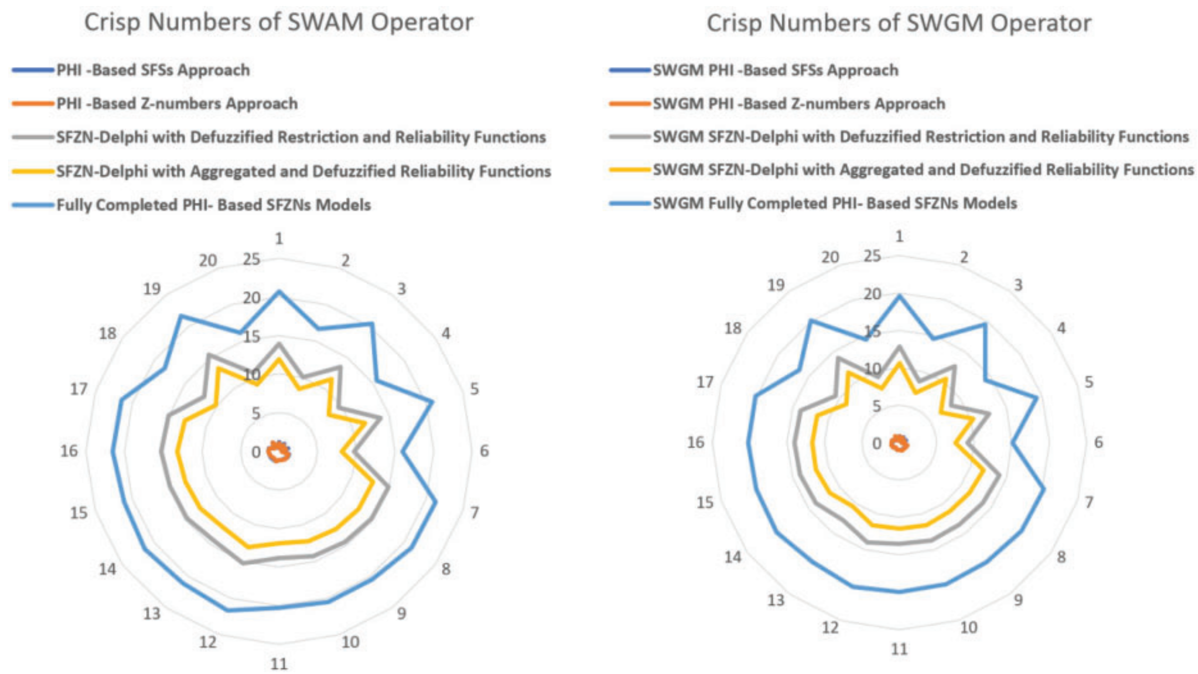

Figure 2: Comparative analysis based on crisp numbers

To comprehensively understand comparative analysis, we used the Spearman correlation to compare the ranking of five approaches. Table 12 presents the correlation of the PHI-Based SFSs Approach with the other approaches, and Table 13 demonstrates the correlation of SFZN-Delphi Using the Z-numbers Approach with the different approaches. The results show that all correlation values above 0.7 indicate a strong relationship among the five approaches. The smallest correlation value of the PHI-Based SFSs Approach with the other approaches is 0.867 and 0.819 with the PHI-Based Z-numbers Approach with the different approaches.

Table 12: The correlation of the PHI-based SFSs approach with the other approaches

PHI-based SFSs approach	Spearman correlation
Using SWAM operator	
PHI-based Z-numbers approach	0.938
SFZN-Delphi with Defuzzified restriction and reliability functions	0.962
SFZN-Delphi with aggregated and defuzzified reliability functions	0.958
Fully completed PHI-based SFZNs models	0.959
Using SWGM operator	
PHI-based Z-numbers approach	0.878
SFZN-Delphi with defuzzified restriction and reliability functions	0.867
SFZN-Delphi with aggregated and defuzzified reliability function	0.896
Fully completed PHI-based SFZNs models	0.934

Table 13: The correlation of PHI-based Z-numbers approach with the other approaches

PHI-based Z-numbers approach	Spearman correlation
Using SWAM operator	
SFZN-Delphi with defuzzified restriction and reliability functions	0.996
SFZN-Delphi with aggregated and defuzzified reliability function	0.996
Fully completed PHI-based SFZNs models	0.819
Using SWGM operator	
SFZN-Delphi with defuzzified restriction and reliability functions	0.940
SFZN-Delphi with aggregated and defuzzified reliability function	0.982
Fully completed PHI-based SFZNs models	0.862

4.3 Discussions

This study combined the advantages of the Spherical Fuzzy Sets and Z-Numbers to develop the new PHI model with two approaches. Based on the results in Section 4.2, the SFS approach indicated 15 appropriate and five rejected barriers in both SWAM and SWGM ways. However, the Z-numbers approach revealed 13 appropriate barriers, seven left barriers in SWAM, and only 12 appropriate barriers and eight rejected barriers to adopting logistics SCM simulation software in Vietnamese universities. The PHI-based Z-numbers approach utilized Kang et al. [29] methodology, which involves converting a Z-number into a fuzzy number. This method is advantageous due to its easy computational and analytic complexity, which permits a broad scope of application. Unfortunately, when Z-numbers are converted to imprecise numbers, a substantial amount of original information is lost, which diminishes the utility of Z-number-based details in its initial situation [30,31]. Therefore, the SFZN-Delphi using the Z-numbers app PHI-based Z-numbers approach roach eliminates more factors than the other method.

In contrast, the PHI-based SFSs approach completely applies the properties of Spherical Fuzzy Sets. Therefore, this method is more complicated than the PHI-based Z-numbers approach due to their equations and operators. In this approach, the researcher utilizes more time and assets to address the MCDM challenges. However, as previously declared regarding the advantages of SFS in Section 1, this method will provide an expanded outcome compared to the app PHI-based Z-numbers approach with a typical spherical observation angle. The data will be thoroughly analyzed to maximize the quality of the information obtained. Depending on the resources and research purposes, researchers can apply appropriate approaches.

Compared with Alkan's methods, the PHI-based SFSs approach has results similar to all three. The similarities between all four methods can be explained by their reliance on the SFS formula. At the same time, their results provide additional evidence to eliminate 5 barriers unsuitable for adopting the logistics SCM simulation software in universities in Vietnam. A set of 15 barriers is confirmed to be the most critical barrier to preventing the process of adopting the logistics SCM simulation software in universities in Vietnam. Each barrier represents a significant obstacle that must be carefully addressed to facilitate successful adoption and integration. High upfront costs (C1) emerge as a prominent barrier, highlighting the financial strain associated with implementing such software solutions. Integration challenges (C3) further complicate matters, indicating the difficulty in seamlessly integrating the software with existing systems and processes. Complexity (C5) underscores the ins and outs involved in navigating and utilizing the software effectively, while data security concerns (C7) raise valid apprehensions regarding protecting sensitive information. Theoretical results (C8) signify a gap between theoretical understanding and practical application, suggesting enhanced training and support mechanisms are needed. Long sales cycles (C9) and implementation time (C10) reflect the prolonged and resource-intensive nature of the adoption process, posing logistical challenges for universities. Computational power (C11) emerges as a critical consideration, highlighting the necessity of robust infrastructure to support the software's functionalities. The lack of industry-specific templates (C12) further exacerbates implementation challenges, necessitating customized solutions tailored to the unique needs of the education sector. The inability to adapt to business changes (C13) underscores the importance of software flexibility and scalability, while opportunity cost (C14) underscores the trade-offs associated with investment in the software. Uncertain ROI (C15) raises doubts regarding the software's potential benefits, emphasizing the need for clear and quantifiable outcomes. The lack of trust (C16) and resistance to change (C17) represent psychological barriers that must be addressed through effective communication and stakeholder engagement. Customization complexity (C19) and automation concerns (C20) highlight technical challenges that must be navigated to ensure smooth adoption and utilization.

5 Conclusions, Implications, Limitations, and Future Research

5.1 Conclusions

The intricacies of information inherently challenge the decision-making process, encompassing complexity, vagueness, and uncertainty. This study represents a pioneering effort in considering the PHI method from dual perspectives, incorporating its restriction and reliability components. Through the presentation of two distinct approaches—the PHI-based SFSs approach and the PHI-based Z-numbers approach—the author adeptly delineates each methodology's primary advantages and limitations. Furthermore, a comprehensive comparative analysis is conducted against three alternative approaches proposed by Alkan et al. [28], underscoring their appropriateness within the context of the study. The outcomes of this comparison reveal noteworthy insights. The SFZN-Delphi, using the Z-numbers approach, encounters 13 barriers when applying SWAM operators and 12 obstacles with SWGM operators, constituting 20 identified barriers in total. Conversely, the PHI-based SFSs approach, integrating both SWAM and SWGM operators, identifies 15 barriers, aligning closely with the proposed research framework. Notably, these findings parallel those observed in SFZN-Delphi with Defuzzified Restriction and Reliability Functions (SWGM operator), SFZN-Delphi with Aggregated and Defuzzified Reliability Function (SWGM operator), and Fully Completed PHI-based SFZNs models across both operator scenarios. This nuanced analysis contributes significantly to understanding decision-making methodologies, offering valuable insights for future research and practical applications.

5.2 Practical Implications

The study's implications are far-reaching, offering valuable insights into enhancing decision-making processes by introducing a new method based on SFSs and Z-numbers. By comparing these approaches with existing methods, the study suggests they can improve decision quality, providing decision-makers with additional tools to navigate complexity, vagueness, and uncertainty. Beyond conventional domains, the interdisciplinary applications of these methodologies span a multitude of fields, including economics, engineering, healthcare, and environmental management. Organizations stand to benefit immensely from leveraging these findings to optimize their strategic decision-making processes, thereby gaining a competitive edge in volatile business environments. Moreover, policymakers can harness the power of advanced decision methodologies to inform policy frameworks, effectively addressing complex societal challenges and enhancing public governance structures. Educational endeavors are crucial in disseminating knowledge and fostering proficiency in applying SFSs and Z-numbers, ensuring their practical utilization in real-world decision-making scenarios.

5.3 Limitations and Future Research

While this study offers significant insights, it is essential to acknowledge its limitations, which should be addressed in future research endeavors. Firstly, the study's exclusive focus on comparing two new PHI methods based on SFSs and Z-numbers may limit its broader applicability by potentially overlooking other relevant decision-making methodologies. Moreover, methodological biases in selecting and implementing comparison methods could impact the efficacy of the proposed approaches. Additionally, the quality and quantity of available data for analysis may influence the validity of the conclusions, emphasizing the necessity for robust data collection and analysis techniques in future studies. Furthermore, the generalizability of the findings might be constrained by the specific context or domain in which they were tested. To mitigate these limitations, future research avenues could explore the integration of SFSs and Z-numbers with other MCDM methods such as DEMATEL, VIKOR, and TOPSIS. Furthermore, applying the proposed approaches to diverse decision-making problems across various industries and domains could enhance their applicability and effectiveness. Refinement of the methodologies to address inherent limitations and biases is also crucial for improving their efficacy. Longitudinal studies could be conducted to assess the long-term impacts of implementing these methodologies in real-world scenarios. Lastly, involving stakeholders in the development and validation process of these methodologies could provide valuable insights and ensure their practical relevance and acceptance.

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