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Distance-based Similarity Measures of Hypersoft Sets under Uncertain Environment and Application in Customer Support Systems

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ABSTRACT

Intuitionistic fuzzy hypersoft sets (IFHSS) represent a novel conceptual framework poised to overcome the limitations associated with intuitionistic fuzzy soft sets (IFSS) concerning the representation of multi-argument domains for parameter approximation. This model offers enhanced flexibility and reliability by facilitating the categorization of parameters into pertinent parametric valued sets. This study investigates the application of the IFHSS theory in enhancing similarity measurement within ChatBot systems. Through experimentation and analysis, the research demonstrates the efficacy of IFHSS-based approaches in handling uncertainties inherent in natural language interactions. We introduce distance measures (DM) along with their corresponding similarity measures (SM). These SMs tailored for IFHSS play a significant role in assessing similarity and facilitating the comparison of various factors. This article aims to develop six SMs based on their DMs and their axiomatic properties, theorems, and illustrative examples. Furthermore, we employ these measures to address real-world problems, particularly in the domain of computer sciences. By leveraging various technical factors, our analysis aids in pinpointing the best ChatBot for the satisfaction of customers. The methodologies proposed in this study hold promise for future case studies involving complex features and multiple decision-makers. Moreover, the suggested approach can be seamlessly integrated with existing structures.

1. Introduction

Data analysis would not been completed without understanding how the dataset's points are related and form trends. Some applications, including text categorization, clustering in recommendation systems, and finding patterns in biological sequences, are dependent on the effort to discover whether data points are similar or dissimilar. Distance measures (DM) and similarity

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measures (SM) are effective tools that tell how much things are similar and how much is the closeness between the objects. SMs help to measure the closeness between things and allow us to uncover new connections and patterns in big data sets. SMs have been as tools in different fields, including artificial intelligence (AI), machine learning (ML), pattern recognition (PR), and information retrieval (IR). Data analysis allows us to explore vast and intricate directories, offering unique insights for wiser decision-making.

This research addresses the delicate realm of SMs and DMs. We will analyze these concepts' essential conceptions, discuss many methodologies of assessment, explore their implementation in different contexts, and lastly talk about their important impact on modern data analysis. Let us walk over the complicated and nuanced elements of these important concepts and unveil how they shine light upon hidden patterns that construct the world of data-driven knowledge around us. Throughout the millennia, humanity has dedicated numerous hours to contemplating the correlation between precision and ambiguity.

It might be challenging to make decisions when the data we work with is inaccurate or unclear at best. To make optimal decisions, it is imperative that we thoroughly examine and select the options that are most probable to provide advantageous outcomes. Multi-attribute decision-making (MADM) facilitates the organization of information in a structured manner and emphasizes important parts in a logical sequence. The fact is that making decisions based on ambiguous information is an inherent aspect of the human experience, occurring at various stages throughout our lives. The primary variables that factor into these situations are data uncertainty, ambiguity, and unreliability [1, 2]. The foundation laid by Atanassov [3] with the creation of a theory of intuitionistic fuzzy sets (IFS) demonstrated the particular members and non-members. Evaluating the level of membership and non-membership is based on assessing the degree to which an element is forthcoming due to the knowledge that we have about its functioning. IFS can be used when the information is vague or not entirely visible. Decision-making without the study of the relation of attributes and alternatives is incomplete. For this, Molodstov [4] proposed the concept of a soft set (SS), which is the parametrized family of sets. SS is a result of a mapping between parameters and the power set of alternatives.

Chen et al. [5] discussed the reduction in the parameters of SS and relevant parameters for the DM techniques. Xu [6] used the concept of IFS to develop MCDM techniques using the concept of SMs. Liang and Shi [7] proposed a new SM and compared the results with some existing SMs and proved that their proposed SMs are more efficient and reliable for DM purposes. Baccour et al. [8] enhanced the concept of SM. Mitchel [9] discussed Dengfeng–Chuntian SMs and applied them to pattern recognition. Ali et al [10] discussed some aggregation operations of SS. Ejegwa et al. [11] applied IFS in career determination. Lee et al. [12] discussed the comparison between interval-valued fuzzy sets and IFS bipolar-valued fuzzy sets. They elaborated on the whole scenarios among all discussed situations. Xu and Chen [13] overviewed the DMs and SMs of IFS and applied the proposed concept to real-life problems. Khorshidi and Nikflazar [14] proposed SMs of generalized fuzzy numbers and applied the proposed concept to risk analysis. Naveed et al. [15] worked on IFS matrices and applied the proposed concept in the selection of laptops.

Decision-making is very crucial in vague and uncertain environments especially when you have disjoint attributes and particularly their sub-attributions. For dealing with MADM structures Samrandache [16] extended the concept of SS into hypersoft sets (HSS) by using multi-argumenta and discussed the attributes with their sub-attributes. HSS structure is more refined and accurate for DM purposes. Jafar and Saeed [17] extended HSS and proposed its aggregation operations like union, intersection, complement, addition, and multiplication. They applied them in mobile selection. Debnath [18] proposed weightage aggregation operations of fuzzy hypersoft sets (FHSS) and proposed a DM algorithm to solve MADM problems. Yolcu and Ozturk [19] applied FHSS to MADM problems. Jafar et al. [20] proposed SM of cosine and cotangent in the intuitionistic fuzzy HSS environment and applied its algorithm in the selection of renewable energy source selection. Jafar et al. [21] proposed Pythagorean fuzzy hypersoft matrices, their aggregations, properties, theorems, and decision-making algorithms. They applied them to the selection of wastewater treatment plants. Saeed et al. [22] proposed q-rung orthopair fuzzy HSS and applied it to passport quality assessment. Harl et al. [23] proposed bipolar picture fuzzy HSS. Saqlain et al. [24, 25] applied HSS structures to real-life problems. Rahman et al. [26] proposed a hypersoft expert set and applied it in the recruitment process. Saqlain et al. [27, 28] proposed single-valued neutrosophic HSSs and their aggregations. They applied the proposed algorithm in the teacher selection process.

An intuitionistic fuzzy HSS combines the aspects of IFSs and HSSs. One must understand each one of these aspects before understanding how they work together. HSSs broaden the fuzzy sets concept by allowing more flexible membership value assignment. The membership degrees in HSSs are not expressed as numerical values but rather using linguistic words or gradations [29, 30]. The method allows a detailed expression of the ambiguity or lack of accuracy [31].

The link between mathematical algorithms (MA) and ML is very deep and necessary. Using ML, we can develop MA and save our calculation time. There is a lot of work in the literature in which researchers proposed linking decision-making algorithms and ML. Edamo et al. [32] gave a comparative analysis of MADM and ML algorithms in flood risk. Maghsoodi et al. [33] presented an ML-driven MADM using LS-SVM feature elimination and applied it to the sustainability performance assessment with incomplete data. Rong et al. [34] proposed a novel MADM method for the evaluation of emergency management schemes under a picture-fuzzy environment. Wang et al. [35] suggested an ML-aided multi-objective optimization and MADM and applied the proposed algorithms in chemical engineering.

The ChatBot customer support system problem is a versatile issue in different banks, companies, business firms, etc. To enhance the response time and accuracy, multiple techniques have been developed. Chakrabortti et al. [36] developed an MCDM technique for the selection of optimum ChatBots for customer service in uncertain environments. Hsu [37] constructed the critical factors for ChatBots and applied mental health services in the army by applying MCDM. Ruan and Mezei [38] discussed about AI ChatBots lead to higher customer satisfaction than humans.

So, there is a gap in the literature on dealing with HSS-SMs using the IFHSS environment, which motivates us to fill that gap and refine the MCDM techniques using IFHSS. Also, a modification is made to the mathematical model and MADM technique to extend the functionality and efficiency of ChatBot systems utilized by customer support and in response to inquiries from consumers, utilizing the framework of a bank's distance-based SMs application. By increasing query comprehension, response accuracy, and overall similarity metrics, this adaptation aims to raise the level of customer satisfaction. In accordance with a predetermined set of specifications, we aimed to develop a chatbot application that employs distance-based SMs to analyze client requests, identify the most relevant responses, and deliver individualized and efficient customer service.

2. Intuitionistic Fuzzy Hypersoft Matrix

Matrices play a vital role in decision-making, especially when we are using an HSS structure. We are going to propose decision-making algorithms using some SMs based on DM, so we have to use matrix representation.

let $\mathcal{Q} = \{\mathcal{Q}_1, \mathcal{Q}_2, \dots, \mathcal{Q}_\alpha\}$ be a set of alternatives with α possibilities, and let $\text{Ⱶ} = \{\text{Ⱶ}_1, \text{Ⱶ}_2, \dots, \text{Ⱶ}_\beta\}$ be a set of disjoint β attributes with their corresponding parametric values of $\text{Ⱶ}_1^a, \text{Ⱶ}_2^b, \dots, \text{Ⱶ}_\beta^z$. An IFHSM is defined in Table 1 with a matrix form as follows:

Table 1
IFHSM of $(\acute{K},\ \digamma_1^a \times \digamma_2^b \times \ldots \times \digamma_\beta^z)$

	$\digamma_1^a$	$\digamma_2^b$	…	$\digamma_\beta^z$
$\mathcal{Q}^1$	$\mathcal{X}_{p_\digamma}(\mathcal{Q}^1, \digamma_1^a)$	$\mathcal{X}_{p_\digamma}(\mathcal{Q}^1, \digamma_2^b)$	…	$\mathcal{X}_{p_\digamma}(\mathcal{Q}^1, \digamma_\beta^z)$
$\mathcal{Q}^2$	$\mathcal{X}_{p_\digamma}(\mathcal{Q}^2, \digamma_1^a)$	$\mathcal{X}_{p_\digamma}(\mathcal{Q}^2, \digamma_2^b)$	…	$\mathcal{X}_{p_\digamma}(\mathcal{Q}^2, \digamma_\beta^z)$
⋮	⋮	⋮	⋱	⋮
$\mathcal{Q}^\alpha$	$\mathcal{X}_{p_\digamma}(\mathcal{Q}^\alpha, \digamma_1^a)$	$\mathcal{X}_{p_\digamma}(\mathcal{Q}^\alpha, \digamma_2^b)$	…	$\mathcal{X}_{p_\digamma}(\mathcal{Q}^\alpha, \digamma_\beta^z)$

If $\zeta_{ij} = \mathcal{X}_{p_\digamma}(\mathcal{Q}^i, \digamma_j^k)$, where $i = 1,2,3 \ldots \alpha$, $j = 1,2,3, \ldots \beta, k = a, b, c, \ldots z$, then a matrix is defined as:

$$[\zeta_{ij}]_{\alpha\times\beta} = \begin{pmatrix} \zeta_{11} & \zeta_{12} & \cdots & \zeta_{1\beta} \\ \zeta_{21} & \zeta_{22} & \cdots & \zeta_{2\beta} \\ \vdots & \vdots & \ddots & \vdots \\ \zeta_{\alpha 1} & \zeta_{\alpha 2} & \cdots & \zeta_{\alpha\beta} \end{pmatrix}, \tag{1}$$

where:

$$\zeta_{ij} = \begin{pmatrix} \left(\mathcal{T}_{\digamma_j^k}(\mathcal{Q}_i), \mathcal{F}_{\digamma_j^k}(\mathcal{Q}_i)\right), \mathcal{Q}_i \in \mathcal{Q} \\ , \digamma_j^k \in \left(\digamma_1^a \times \digamma_2^b \times \ \ldots \ \times \digamma_\beta^z\right) \end{pmatrix} = \left(\mathcal{T}_{\digamma_j^k}(\mathcal{Q}_i), \mathcal{F}_{\digamma_j^k}(\mathcal{Q}_i)\right). \tag{2}$$

For simplicity, we can suppose that $\mathcal{T}_{\digamma_j^k}(\mathcal{Q}_i) = \mathcal{T}_{ij}$ and $\mathcal{F}_{\digamma_j^k}(\mathcal{Q}_i) = \mathcal{F}_{ij}$, where i is the position of alternatives, j is the attributes, hidden k given the information of its sub-attributive value of the corresponding attribute. Thus, the matrix representation is as:

$$\mathcal{M}_{\alpha\times\beta} = \begin{bmatrix} (\mathcal{T}_{11}, \mathcal{F}_{11}) & (\mathcal{T}_{12}, \mathcal{F}_{12}) & \cdots & (\mathcal{T}_{1\beta}, \mathcal{F}_{1\beta}) \\ (\mathcal{T}_{21}, \mathcal{F}_{21}) & (\mathcal{T}_{22}, \mathcal{F}_{22}) & \cdots & (\mathcal{T}_{2\beta}, \mathcal{F}_{2\beta}) \\ \vdots & \vdots & \vdots & \vdots \\ (\mathcal{T}_{\alpha 1}, \mathcal{F}_{\alpha 1}) & (\mathcal{T}_{\alpha 2}, \mathcal{F}_{\alpha 2}) & \cdots & (\mathcal{T}_{\alpha\beta}, \mathcal{F}_{\alpha\beta}) \end{bmatrix}. \tag{3}$$

2.1 Aggregations of Intuitionistic Fuzzy Hypersoft Matrices

Let $\mathcal{M} = [\mathcal{T}_{ij}^{\mathcal{M}}, \mathcal{F}_{ij}^{\mathcal{M}}]$ and $\mathcal{N} = [\mathcal{T}_{ij}^{\mathcal{N}}, \mathcal{F}_{ij}^{\mathcal{N}}] \in \mathrm{IFHSM}_{\alpha\times\beta}$ be the two IFHSMs of order $\alpha \times \beta$. Then, with the conditions $0 \le \mathcal{T}_\digamma^{\mathcal{M}}(\mathcal{Q}_\tau) + \mathcal{F}_\digamma^{\mathcal{M}}(\mathcal{Q}_\tau) \le 1$ and $0 \le \mathcal{T}_\digamma^{\mathcal{N}}(\mathcal{Q}_\tau) + \mathcal{F}_\digamma^{\mathcal{N}}(\mathcal{Q}_\tau) \le 1$, we have the following:

i. *Union of two IFHSMs:*

$$\mathcal{M} \cup \mathcal{N} = \left[\boldsymbol{max}\left(\mathcal{T}_{ij}^{\mathcal{M}}, \mathcal{T}_{ij}^{\mathcal{N}}\right), \boldsymbol{min}\left(\mathcal{F}_{ij}^{\mathcal{M}}, \mathcal{F}_{ij}^{\mathcal{N}}\right)\right], \forall\, i, j. \tag{4}$$

ii. *Intersection of two IFHSMs:*

$$\mathcal{M} \cap \mathcal{N} = \left[\boldsymbol{min}\left(\mathcal{T}_{ij}^{\mathcal{M}}, \mathcal{T}_{ij}^{\mathcal{N}}\right), \boldsymbol{max}\left(\mathcal{F}_{ij}^{\mathcal{M}}, \mathcal{F}_{ij}^{\mathcal{N}}\right)\right], \forall\, i, j. \tag{5}$$

iii. *Product of two IFHSMs:*

$$\boldsymbol{\mathcal{M}}.\boldsymbol{\mathcal{N}} = \left[\left(\boldsymbol{\mathcal{T}}_{ij}^{\mathcal{M}}.\boldsymbol{\mathcal{T}}_{ij}^{\mathbf{N}}, \boldsymbol{\mathcal{F}}_{ij}^{\mathcal{M}} + \boldsymbol{\mathcal{F}}_{ij}^{\mathcal{N}} - \boldsymbol{\mathcal{F}}_{ij}^{\mathcal{M}}.\boldsymbol{\mathcal{F}}_{ij}^{\mathcal{N}}\right)\right], \forall\, \boldsymbol{i}, \boldsymbol{j}. \tag{6}$$

iv. *Addition of two IFHSMs:*

$$\boldsymbol{\mathcal{M}} + \boldsymbol{\mathcal{N}} = \left[\left(\boldsymbol{\mathcal{T}}_{ij}^{\mathcal{M}} + \boldsymbol{\mathcal{T}}_{ij}^{\mathbf{N}} - \boldsymbol{\mathcal{T}}_{i+j}^{\mathcal{M}}.\boldsymbol{\mathcal{T}}_{ij}^{\mathbf{N}}, \boldsymbol{\mathcal{F}}_{ij}^{\mathcal{M}}.\boldsymbol{\mathcal{F}}_{ij}^{\mathbf{N}}\right)\right], \forall\, \boldsymbol{i}, \boldsymbol{j}. \tag{7}$$

2.2 MADM algorithm based on Intuitionistic Fuzzy Hypersoft Matrices

By utilizing the defined choice and weighted choices matrices, we present the IFHSM algorithm. Let $\mathcal{M} = \left[\mathcal{T}_{ij}^{\mathcal{M}}, \mathcal{F}_{ij}^{\mathcal{M}}\right] \in \mathrm{IFHSM}_{\alpha\times\beta}$. The choice matrix can be defined as:

$$\mathbb{C}(\boldsymbol{\mathcal{M}}) = \left[\left(\frac{\sum_{j=1}^{n}\boldsymbol{\mathcal{T}}_{ij}^{\mathcal{M}}}{\boldsymbol{n}}, \frac{\sum_{j=1}^{n}\boldsymbol{\mathcal{F}}_{ij}^{\mathcal{M}}}{\boldsymbol{n}}\right)\right]_{\boldsymbol{m}\times\mathbf{1}}, \forall\, \boldsymbol{i}. \tag{8}$$

Let $\mathcal{M} = \left[\mathcal{T}_{ij}^{\mathcal{M}}, \mathcal{F}_{ij}^{\mathcal{M}}\right] \in \mathrm{IFHSM}_{\alpha\times\beta}$. The weighted choice matrix is defined as:

$$\mathbb{C}(\boldsymbol{\mathcal{M}}) = \left[\left(\frac{\sum_{j=1}^{n}\boldsymbol{\omega}_j\boldsymbol{\mathcal{T}}_{ij}^{\mathcal{M}}}{\sum\boldsymbol{\omega}_j}, \frac{\sum_{j=1}^{n}\boldsymbol{\omega}_j\boldsymbol{\mathcal{F}}_{ij}^{\mathcal{M}}}{\sum\boldsymbol{\omega}_j}\right)\right]_{\boldsymbol{m}\times\mathbf{1}}, \forall\, \boldsymbol{i}. \tag{9}$$

2.3 Distance Measures for Intuitionistic Fuzzy Hypersoft Matrices

This work encompasses a substantial array of novel formulas for distances in IHSSs. These theorems and characteristics originate from the fundamental concept of distance within IHSSs.

A distance measure is a real-valued function $d: \beta(\mathbb{Y}) \times \beta(\mathbb{Y}) \to [0,1]$, where d meets the following axioms for $\mathcal{P}, \mathcal{Q}$, and $\mathcal{R} \subseteq \beta(\mathbb{Y})$:

i. $0 \le d(\mathcal{P},\mathcal{Q}) \le 1$ (D1).
ii. $d(\mathcal{P},\mathcal{Q}) = 0$ Iff $\mathcal{P} = \mathcal{Q}$ (D2).
iii. $d(\mathcal{P},\mathcal{Q}) = d(\mathcal{Q},\mathcal{P}) /*$ (D3).
iv. $\mathcal{P} \subseteq \mathcal{Q} \subseteq \mathcal{R}$ so $d(\mathcal{P},\mathcal{R}) \ge d(\mathcal{Q},\mathcal{R})$ and $d(\mathcal{P},\mathcal{R}) \ge d(\mathcal{P},\mathcal{Q})$ (D4).

Theorem 1. $d^k(\mathcal{P},\mathcal{Q})$ for $k = 1, 2, \ldots, 6$ is a distance between IFHSSs $\mathcal{P}$ and $\mathcal{Q}$ as:

$$\boldsymbol{d}^{\mathbf{1}}(\boldsymbol{\mathcal{P}},\boldsymbol{\mathcal{Q}}) = \frac{\mathbf{1}}{\mathbf{2}|\mathbb{Y}|}\sum_{\boldsymbol{\tau}}\left(\left|\boldsymbol{\mathcal{T}}_{\mathcal{P}}^{2}(\boldsymbol{\Psi}(\boldsymbol{\upsilon}))_{\boldsymbol{\tau}} - \boldsymbol{\mathcal{T}}_{\mathcal{Q}}^{2}(\boldsymbol{\Psi}(\boldsymbol{\upsilon}))_{\boldsymbol{\tau}}\right| + \left|\boldsymbol{\mathcal{F}}_{\mathcal{P}}^{2}(\boldsymbol{\Psi}(\boldsymbol{\upsilon}))_{\boldsymbol{\tau}} - \boldsymbol{\mathcal{F}}_{\mathcal{Q}}^{2}(\boldsymbol{\Psi}(\boldsymbol{\upsilon}))_{\boldsymbol{\tau}}\right|\right), \tag{10}$$

$$\boldsymbol{d}^{\mathbf{2}}(\boldsymbol{\mathcal{P}},\boldsymbol{\mathcal{Q}}) = \frac{\mathbf{1}}{\mathbf{2}|\mathbb{Y}|}\sum_{\boldsymbol{\tau}}\left|\left(\boldsymbol{\mathcal{T}}_{\mathcal{P}}^{2}(\boldsymbol{\Psi}(\boldsymbol{\upsilon}))_{\boldsymbol{\tau}} - \boldsymbol{\mathcal{T}}_{\mathcal{Q}}^{2}(\boldsymbol{\Psi}(\boldsymbol{\upsilon}))_{\boldsymbol{\tau}} - \left(\boldsymbol{\mathcal{F}}_{\mathcal{P}}^{2}(\boldsymbol{\Psi}(\boldsymbol{\upsilon}))_{\boldsymbol{\tau}} - \boldsymbol{\mathcal{F}}_{\mathcal{Q}}^{2}(\boldsymbol{\Psi}(\boldsymbol{\upsilon}))_{\boldsymbol{\tau}}\right)\right|\right), \tag{11}$$

$$\boldsymbol{d}^{\mathbf{3}}(\boldsymbol{\mathcal{P}},\boldsymbol{\mathcal{Q}}) = \frac{\mathbf{1}}{\mathbf{2}|\mathbb{Y}|}\sum_{\boldsymbol{\tau}}\left(\left|\boldsymbol{\mathcal{T}}_{\mathcal{P}}^{2}(\boldsymbol{\Psi}(\boldsymbol{\upsilon}))_{\boldsymbol{\tau}} - \boldsymbol{\mathcal{T}}_{\mathcal{Q}}^{2}(\boldsymbol{\Psi}(\boldsymbol{\upsilon}))_{\boldsymbol{\tau}}\right| \vee \left|\boldsymbol{\mathcal{F}}_{\mathcal{P}}^{2}(\boldsymbol{\Psi}(\boldsymbol{\upsilon}))_{\boldsymbol{\tau}} - \boldsymbol{\mathcal{F}}_{\mathcal{Q}}^{2}(\boldsymbol{\Psi}(\boldsymbol{\upsilon}))_{\boldsymbol{\tau}}\right|\right), \tag{12}$$

$$\boldsymbol{d}^{\mathbf{4}}(\boldsymbol{\mathcal{P}},\boldsymbol{\mathcal{Q}}) = \frac{\sum_{\boldsymbol{\tau}}\left(\left|\boldsymbol{\mathcal{T}}_{\mathcal{P}}^{2}(\boldsymbol{\Psi}(\boldsymbol{\upsilon}))_{\boldsymbol{\tau}} - \boldsymbol{\mathcal{T}}_{\mathcal{Q}}^{2}(\boldsymbol{\Psi}(\boldsymbol{\upsilon}))_{\boldsymbol{\tau}}\right| \vee \left|\boldsymbol{\mathcal{F}}_{\mathcal{P}}^{2}(\boldsymbol{\Psi}(\boldsymbol{\upsilon}))_{\boldsymbol{\tau}} - \boldsymbol{\mathcal{F}}_{\mathcal{Q}}^{2}(\boldsymbol{\Psi}(\boldsymbol{\upsilon}))_{\boldsymbol{\tau}}\right|\right)}{\sum_{\boldsymbol{\tau}}\left(\mathbf{1} + \left(\left|\boldsymbol{\mathcal{T}}_{\mathcal{P}}^{2}(\boldsymbol{\Psi}(\boldsymbol{\upsilon}))_{\boldsymbol{\tau}} - \boldsymbol{\mathcal{T}}_{\mathcal{Q}}^{2}(\boldsymbol{\Psi}(\boldsymbol{\upsilon}))_{\boldsymbol{\tau}}\right| \vee \left|\boldsymbol{\mathcal{F}}_{\mathcal{P}}^{2}(\boldsymbol{\Psi}(\boldsymbol{\upsilon}))_{\boldsymbol{\tau}} - \boldsymbol{\mathcal{F}}_{\mathcal{Q}}^{2}(\boldsymbol{\Psi}(\boldsymbol{\upsilon}))_{\boldsymbol{\tau}}\right|\right)\right)}, \tag{13}$$

$$\boldsymbol{d^5(\mathcal{P},\mathcal{Q}) = 1 - \alpha \frac{\sum_\tau \left(\mathcal{T}_\mathcal{P}^2(\Psi(\upsilon))_\tau \wedge \mathcal{T}_\mathcal{Q}^2(\Psi(\upsilon))_\tau\right)}{\sum_\tau \left(\mathcal{T}_\mathcal{P}^2(\Psi(\upsilon))_\tau \vee \mathcal{T}_\mathcal{Q}^2(\Psi(\upsilon))_\tau\right)} - \gamma \frac{\sum_\tau \left(\mathcal{F}_\mathcal{P}^2(\Psi(\upsilon))_\tau \wedge \mathcal{F}_\mathcal{Q}^2(\Psi(\upsilon))_\tau\right)}{\sum_\tau \left(\mathcal{F}_\mathcal{P}^2(\Psi(\upsilon))_\tau \vee \mathcal{F}_\mathcal{Q}^2(\Psi(\upsilon))_\tau\right)},} \tag{14}$$

$$\boldsymbol{d^6(\mathcal{P},\mathcal{Q}) = 1 - \frac{\alpha}{|\mathbb{Y}|} \sum_\tau \frac{\left(\mathcal{T}_\mathcal{P}^2(\Psi(\upsilon))_\tau \wedge \mathcal{T}_\mathcal{Q}^2(\Psi(\upsilon))_\tau\right)}{\left(\mathcal{T}_\mathcal{P}^2(\Psi(\upsilon))_\tau \vee \mathcal{T}_\mathcal{Q}^2(\Psi(\upsilon))_\tau\right)} - \frac{\gamma}{|\mathbb{Y}|} \sum_\tau \frac{\left(\mathcal{F}_\mathcal{P}^2(\Psi(\upsilon))_\tau \wedge \mathcal{F}_\mathcal{Q}^2(\Psi(\upsilon))_\tau\right)}{\left(\mathcal{F}_\mathcal{P}^2(\Psi(\upsilon))_\tau \vee \mathcal{F}_\mathcal{Q}^2(\Psi(\upsilon))_\tau\right)},} \tag{15}$$

where $\alpha + \gamma = 1$ and $\alpha, \gamma \in [0,1]$.

In the light of $(\mathrm{D}_1) - (\mathrm{D}_3)$ for $d^{\grave{k}}(\mathcal{P},\mathcal{Q})$ ($\grave{k}$ = 1, 2, …,6) if $d^{\grave{k}}(\mathcal{P},\mathcal{Q})$ obey all of the distance's axioms, they are valid.

Theorem 2. Let $\mathcal{P}$ and $\mathcal{Q}$ be two IFHSSs, then $d^k(\mathcal{P},\mathcal{Q})$ for k=1, 2,…,6. Then, $d^k(\mathcal{P},\mathcal{Q})$ holds the following:

i. $d^k(\mathcal{P},\mathcal{Q}^c) = d^k(\mathcal{P}^c,\mathcal{Q})$.
ii. $d^k(\mathcal{P},\mathcal{Q}) = d^k(\mathcal{P}\cap\mathcal{Q},\mathcal{P}\cup\mathcal{Q})$.
iii. $d^k(\mathcal{P},\mathcal{P}\cap\mathcal{Q}) = d^k(\mathcal{Q},\mathcal{P}\cup\mathcal{Q})$.
iv. $d^k(\mathcal{P},\mathcal{P}\cup\mathcal{Q}) = d^k(\mathcal{Q},\mathcal{P}\cap\mathcal{Q})$.

Proof of Theorem 2.

i. $d^k(\mathcal{P},\mathcal{Q}^c) = d^k(\mathcal{P}^c,\mathcal{Q})$.

Let $\mathcal{P} = \left\{\langle \mathcal{T}_\mathcal{P}(\Psi(\upsilon))_\tau, \mathcal{F}_\mathcal{P}(\Psi(\upsilon))_\tau, \rangle\right\}$, $\mathcal{Q} = \left\{\langle \mathcal{T}_\mathcal{Q}(\Psi(\upsilon))_\tau, \mathcal{F}_\mathcal{Q}(\Psi(\upsilon))_\tau \rangle\right\}$, and $\mathcal{Q}^c = \left\{\langle \mathcal{F}_\mathcal{Q}(\Psi(\upsilon))_\tau, \mathcal{T}_\mathcal{Q}(\Psi(\upsilon))_\tau \rangle\right\}$. Then, we have:

$$d^1(\mathcal{P},\mathcal{Q}) = \frac{1}{2|\mathbb{Y}|}\sum_\tau \left(\left|\mathcal{T}_\mathcal{P}^2(\Psi(\upsilon))_\tau - \mathcal{T}_\mathcal{Q}^2(\Psi(\upsilon))_\tau\right| + \left|\mathcal{F}_\mathcal{P}^2(\Psi(\upsilon))_\tau - \mathcal{F}_\mathcal{Q}^2(\Psi(\upsilon))_\tau\right|\right),$$

$$d^1(\mathcal{P},\mathcal{Q}^c) = \frac{1}{2|\mathbb{Y}|}\sum_\tau \left(\left|\mathcal{T}_\mathcal{P}^2(\Psi(\upsilon))_\tau - \mathcal{F}_\mathcal{Q}^2(\Psi(\upsilon))_\tau\right| + \left|\mathcal{F}_\mathcal{P}^2(\Psi(\upsilon))_\tau - \mathcal{T}_\mathcal{Q}^2(\Psi(\upsilon))_\tau\right|\right) = d^1(\mathcal{P}^c,\mathcal{Q}).$$

ii. $d^k(\mathcal{P},\mathcal{Q}) = d^k(\mathcal{P}\cap\mathcal{Q},\mathcal{P}\cup\mathcal{Q})$.

We have:

$$d^1(\mathcal{P},\mathcal{Q}) = d^1(\mathcal{P}\cap\mathcal{Q},\mathcal{P}\cup\mathcal{Q})$$
$$= \frac{1}{2|\mathbb{Y}|}\sum_\tau \left(\left|\left(\min\left(\mathcal{T}_\mathcal{P}(\Psi(\upsilon)),\mathcal{T}_\mathcal{Q}(\Psi(\upsilon))\right)\right)^2 - \left(\max\left(\mathcal{T}_\mathcal{P}(\Psi(\upsilon)),\mathcal{T}_\mathcal{Q}(\Psi(\upsilon))\right)\right)^2\right|\right.$$
$$\left. + \left|\left(\max\left(\mathcal{F}_\mathcal{P}(\Psi(\upsilon)),\mathcal{F}_\mathcal{Q}(\Psi(\upsilon))\right)\right)^2 - \left(\min\left(\mathcal{F}_\mathcal{P}(\Psi(\upsilon)),\mathcal{F}_\mathcal{Q}(\Psi(\upsilon))\right)\right)^2\right|\right.$$
$$= \frac{1}{2|\mathbb{Y}|}\sum_\tau \left(\left|\mathcal{T}_\mathcal{P}^2(\Psi(\upsilon))_\tau - \mathcal{T}_\mathcal{Q}^2(\Psi(\upsilon))_\tau\right| + \left|\mathcal{F}_\mathcal{P}^2(\Psi(\upsilon))_\tau - \mathcal{F}_\mathcal{Q}^2(\Psi(\upsilon))_\tau\right|\right) = d^1(\mathcal{P},\mathcal{Q}).$$

iii. $d^k(\mathcal{P},\mathcal{P}\cap\mathcal{Q}) = d^k(\mathcal{Q},\mathcal{P}\cup\mathcal{Q})$.

We have:

$$d^1(\mathcal{P},\mathcal{P}\cap\mathcal{Q}) = d^1(\mathcal{Q},\mathcal{P}\cup\mathcal{Q})$$
$$= \frac{1}{2|\mathbb{Y}|}\sum_{\tau}\left(\left|\mathcal{T}_{\mathcal{P}}^2(\Psi(\upsilon)) - \left(\min\left(\mathcal{T}_{\mathcal{P}}(\Psi(\upsilon)),\mathcal{T}_{\mathcal{Q}}(\Psi(\upsilon))\right)\right)^2\right| + \left|\mathcal{F}_{\mathcal{P}}^2(\Psi(\upsilon)) - \left(\max\left(\mathcal{F}_{\mathcal{P}}(\Psi(\upsilon)),\mathcal{F}_{\mathcal{Q}}(\Psi(\upsilon))\right)\right)^2\right|\right.$$
$$= d^1(\mathcal{Q},\mathcal{P}\cup\mathcal{Q}).$$

These proofs' steps for (*iii*) and (*iv*) are comparable, making it possible to verify them similarly.

2.4 Similarity Measures for Intuitionistic Fuzzy Hypersoft Matrices

Consider $\mathcal{P}$ and $\mathcal{Q}$ as two IFHSSs, and let S be a mapping denoted as $S:\beta(\mathbb{Y})\times\beta(\mathbb{Y})\to[0,1]$, termed a similarity measure between $\mathcal{P}$ and $\mathcal{Q}$ if S fulfills the subsequent axioms for $\mathcal{P},\mathcal{Q},$ and $\mathcal{R}\subseteq\beta(\mathbb{Y})$:

i. $0\le S(\mathcal{P},\mathcal{Q})\le 1$ (S1).
ii. $S(\mathcal{P},\mathcal{Q})=0$ If and only if $\mathcal{P}=\mathcal{Q}$ (S2).
iii. $S(\mathcal{P},\mathcal{Q})=S(\mathcal{Q},\mathcal{P})$ (S3).
iv. $\mathcal{P}\subseteq\mathcal{Q}\subseteq\mathcal{R}$, then $S(\mathcal{P},\mathcal{R})\le S(\mathcal{P},\mathcal{Q})$ and $S(\mathcal{P},\mathcal{R})\le S(\mathcal{Q},\mathcal{R})$ (S4).

Theorem 3. Let $\mathcal{P}$ and $\mathcal{Q}$ be two IFHSSs. Then, $S^{\grave{k}}(\mathcal{P},\mathcal{Q})$ for $\grave{k}=1,2,3\ldots 6$, are SMs as:

$$\boldsymbol{S^1(\mathcal{P},\mathcal{Q}) = 1-\frac{1}{2|\mathbb{Y}|}\sum_\tau\left(\left|\mathcal{T}_{\mathcal{P}}^2(\Psi(\upsilon))_\tau-\mathcal{T}_{\mathcal{Q}}^2(\Psi(\upsilon))_\tau\right|+\left|\mathcal{F}_{\mathcal{P}}^2(\Psi(\upsilon))_\tau-\mathcal{F}_{\mathcal{Q}}^2(\Psi(\upsilon))_\tau\right|\right)}, \tag{16}$$

$$\boldsymbol{S^2(\mathcal{P},\mathcal{Q}) = 1-\frac{1}{2|\mathbb{Y}|}\sum_\tau\left|\left(\mathcal{T}_{\mathcal{P}}^2(\Psi(\upsilon))_\tau-\mathcal{T}_{\mathcal{Q}}^2(\Psi(\upsilon))_\tau-\left(\mathcal{F}_{\mathcal{P}}^2(\Psi(\upsilon))_\tau-\mathcal{F}_{\mathcal{Q}}^2(\Psi(\upsilon))_\tau\right)\right|\right)}, \tag{17}$$

$$\boldsymbol{S^3(\mathcal{P},\mathcal{Q}) = 1-\frac{1}{|\mathbb{Y}|}\sum_\tau\left(\left|\mathcal{T}_{\mathcal{P}}^2(\Psi(\upsilon))_\tau-\mathcal{T}_{\mathcal{Q}}^2(\Psi(\upsilon))_\tau\right|\vee\left|\mathcal{F}_{\mathcal{P}}^2(\Psi(\upsilon))_\tau-\mathcal{F}_{\mathcal{Q}}^2(\Psi(\upsilon))_\tau\right|\right)}, \tag{18}$$

$$\boldsymbol{S^4(\mathcal{P},\mathcal{Q}) = \frac{\sum_\tau 1-\left(\left|\mathcal{T}_{\mathcal{P}}^2(\Psi(\upsilon))_\tau-\mathcal{T}_{\mathcal{Q}}^2(\Psi(\upsilon))_\tau\right|\vee\left|\mathcal{F}_{\mathcal{P}}^2(\Psi(\upsilon))_\tau-\mathcal{F}_{\mathcal{Q}}^2(\Psi(\upsilon))_\tau\right|\right)}{\sum_\tau\left(1+\left(\left|\mathcal{T}_{\mathcal{P}}^2(\Psi(\upsilon))_\tau-\mathcal{T}_{\mathcal{Q}}^2(\Psi(\upsilon))_\tau\right|\vee\left|\mathcal{F}_{\mathcal{P}}^2(\Psi(\upsilon))_\tau-\mathcal{F}_{\mathcal{Q}}^2(\Psi(\upsilon))_\tau\right|\right)\right)}}, \tag{19}$$

$$\boldsymbol{S^5(\mathcal{P},\mathcal{Q}) = \alpha\frac{\sum_\tau\left(\mathcal{T}_{\mathcal{P}}^2(\Psi(\upsilon))_\tau\wedge\mathcal{T}_{\mathcal{Q}}^2(\Psi(\upsilon))_\tau\right)}{\sum_\tau\left(\mathcal{T}_{\mathcal{P}}^2(\Psi(\upsilon))_\tau\vee\mathcal{T}_{\mathcal{Q}}^2(\Psi(\upsilon))_\tau\right)}+\gamma\frac{\sum_\tau\left(\mathcal{F}_{\mathcal{P}}^2(\Psi(\upsilon))_\tau\wedge\mathcal{F}_{\mathcal{Q}}^2(\Psi(\upsilon))_\tau\right)}{\sum_\tau\left(\mathcal{F}_{\mathcal{P}}^2(\Psi(\upsilon))_\tau\vee\mathcal{F}_{\mathcal{Q}}^2(\Psi(\upsilon))_\tau\right)}}, \tag{20}$$

$$\boldsymbol{S^6(\mathcal{P},\mathcal{Q}) = \frac{\alpha}{|\mathbb{Y}|}\sum_\tau\frac{\left(\mathcal{T}_{\mathcal{P}}^2(\Psi(\upsilon))_\tau\wedge\mathcal{T}_{\mathcal{Q}}^2(\Psi(\upsilon))_\tau\right)}{\left(\mathcal{T}_{\mathcal{P}}^2(\Psi(\upsilon))_\tau\vee\mathcal{T}_{\mathcal{Q}}^2(\Psi(\upsilon))_\tau\right)}+\frac{\gamma}{|\mathbb{Y}|}\sum_\tau\frac{\left(\mathcal{F}_{\mathcal{P}}^2(\Psi(\upsilon))_\tau\wedge\mathcal{F}_{\mathcal{Q}}^2(\Psi(\upsilon))_\tau\right)}{\left(\mathcal{F}_{\mathcal{P}}^2(\Psi(\upsilon))_\tau\vee\mathcal{F}_{\mathcal{Q}}^2(\Psi(\upsilon))_\tau\right)}}, \tag{21}$$

where $\alpha+\gamma=1$ and $\alpha,\gamma\,\epsilon[0,1]$.

S_1, S_3, and S_4 are self-evident, so we will solely demonstrate the criteria for S_2. For brevity, we will only provide the proof of $S^k(\mathcal{P},\mathcal{Q})$ for $k=1$, with proofs for $k=2,3,\ldots,6$ following a similar approach. So, for $k=1$, $S^k(\mathcal{P},\mathcal{Q})$ is:

$$S^1(\mathcal{P},\mathcal{Q}) = 1-\frac{1}{2|\mathbb{Y}|}\sum_\tau\left(\left|\mathcal{T}_{\mathcal{P}}^2(\Psi(\upsilon))_\tau-\mathcal{T}_{\mathcal{Q}}^2(\Psi(\upsilon))_\tau\right|+\left|\mathcal{F}_{\mathcal{P}}^2(\Psi(\upsilon))_\tau-\mathcal{F}_{\mathcal{Q}}^2(\Psi(\upsilon))_\tau\right|\right).$$

$S^1(\mathcal{P},\mathcal{Q})=1$ if and only if $\mathcal{P}=\mathcal{Q}$:

$$1-\frac{1}{|\mathbb{Y}|}\sum_\tau\left(\left|\mathcal{T}_{\mathcal{P}}^2(\Psi(\upsilon))_\tau-\mathcal{T}_{\mathcal{Q}}^2(\Psi(\upsilon))_\tau\right|+\left|\mathcal{F}_{\mathcal{P}}^2(\Psi(\upsilon))_\tau-\mathcal{F}_{\mathcal{Q}}^2(\Psi(\upsilon))_\tau\right|\right)=1$$

$(\Rightarrow)\sum_{\tau}\left(\left|\mathcal{T}_{\mathcal{P}}^{2}(\Psi(\upsilon))_{\tau}-\mathcal{T}_{\mathcal{Q}}^{2}(\Psi(\upsilon))_{\tau}\right|+\left|\mathcal{F}_{\mathcal{P}}^{2}(\Psi(\upsilon))_{\tau}-\mathcal{F}_{\mathcal{Q}}^{2}(\Psi(\upsilon))_{\tau}\right|\right)=0.$

($\Rightarrow$) which is only possible when:

$\left|\mathcal{T}_{\mathcal{P}}^{2}(\Psi(\upsilon))_{\tau}-\mathcal{T}_{\mathcal{Q}}^{2}(\Psi(\upsilon))_{\tau}\right|+\left|\mathcal{F}_{\mathcal{P}}^{2}(\Psi(\upsilon))_{\tau}-\mathcal{F}_{\mathcal{Q}}^{2}(\Psi(\upsilon))_{\tau}\right|\Big)=0$

$(\Rightarrow)\left|\mathcal{T}_{\mathcal{P}}^{2}(\Psi(\upsilon))_{\tau}-\mathcal{T}_{\mathcal{Q}}^{2}(\Psi(\upsilon))_{\tau}\right|=0,\left|\mathcal{F}_{\mathcal{P}}^{2}(\Psi(\upsilon))_{\tau}-\mathcal{F}_{\mathcal{Q}}^{2}(\Psi(\upsilon))_{\tau}\right|\Big)=0$

$(\Rightarrow)\mathcal{T}_{\mathcal{P}}^{2}(\Psi(\upsilon))_{\tau}-\mathcal{T}_{\mathcal{Q}}^{2}(\Psi(\upsilon))_{\tau}=0,\mathcal{F}_{\mathcal{P}}^{2}(\Psi(\upsilon))_{\tau}-\mathcal{F}_{\mathcal{Q}}^{2}(\Psi(\upsilon))_{\tau}=0$

$(\Rightarrow)\mathcal{T}_{\mathcal{P}}^{2}(\Psi(\upsilon))_{\tau}=\mathcal{T}_{\mathcal{Q}}^{2}(\Psi(\upsilon))_{\tau},\mathcal{F}_{\mathcal{P}}^{2}(\Psi(\upsilon))_{\tau}=\mathcal{F}_{\mathcal{Q}}^{2}(\Psi(\upsilon))_{\tau}$

$\mathcal{T}_{\mathcal{P}}(\Psi(\upsilon))_{\tau}=\mathcal{T}_{\mathcal{Q}}(\Psi(\upsilon))_{\tau},\mathcal{F}_{\mathcal{P}}(\Psi(\upsilon))_{\tau}=\mathcal{F}_{\mathcal{Q}}(\Psi(\upsilon))_{\tau}$

$(\Rightarrow)\mathcal{P}=\mathcal{Q}.$

Conversely, if $\mathcal{P}=\mathcal{Q}$, we aim to demonstrate that $S^{1}(\mathcal{P},\mathcal{Q})=1$. Given $\mathcal{P}=\mathcal{Q}$ this implies:

$(\Leftarrow)\mathcal{T}_{\mathcal{P}}(\Psi(\upsilon))_{\tau}=\mathcal{T}_{\mathcal{Q}}(\Psi(\upsilon))_{\tau},\mathcal{F}_{\mathcal{P}}(\Psi(\upsilon))_{\tau}=\mathcal{F}_{\mathcal{Q}}(\Psi(\upsilon))_{\tau}$

$(\Leftarrow)\mathcal{T}_{\mathcal{P}}^{2}(\Psi(\upsilon))_{\tau}=\mathcal{T}_{\mathcal{Q}}^{2}(\Psi(\upsilon))_{\tau},\mathcal{F}_{\mathcal{P}}^{2}(\Psi(\upsilon))_{\tau}=\mathcal{F}_{\mathcal{Q}}^{2}(\Psi(\upsilon))_{\tau}$

$(\Leftarrow)\mathcal{T}_{\mathcal{P}}^{2}(\Psi(\upsilon))_{\tau}-\mathcal{T}_{\mathcal{Q}}^{2}(\Psi(\upsilon))_{\tau}=0,$

$\mathcal{F}_{\mathcal{P}}^{2}(\Psi(\upsilon))_{\tau}-\mathcal{F}_{\mathcal{Q}}^{2}(\Psi(\upsilon))_{\tau}=0$

$(\Leftarrow)\left|\mathcal{T}_{\mathcal{P}}^{2}(\Psi(\upsilon))_{\tau}-\mathcal{T}_{\mathcal{Q}}^{2}(\Psi(\upsilon))_{\tau}\right|=0,$

$,\left|\mathcal{F}_{\mathcal{P}}^{2}(\Psi(\upsilon))_{\tau}-\mathcal{F}_{\mathcal{Q}}^{2}(\Psi(\upsilon))_{\tau}\right|\Big)=0$

$(\Leftarrow)\frac{1}{2|\mathbb{Y}|}\sum_{\tau}\left(\left|\mathcal{T}_{\mathcal{P}}^{2}(\Psi(\upsilon))_{\tau}-\mathcal{T}_{\mathcal{Q}}^{2}(\Psi(\upsilon))_{\tau}\right|+\left|\mathcal{F}_{\mathcal{P}}^{2}(\Psi(\upsilon))_{\tau}-\mathcal{F}_{\mathcal{Q}}^{2}(\Psi(\upsilon))_{\tau}\right|\right)=0$

$(\Leftarrow)1-\frac{1}{2|\mathbb{Y}|}\sum_{\tau}\left(\left|\mathcal{T}_{\mathcal{P}}^{2}(\Psi(\upsilon))_{\tau}-\mathcal{T}_{\mathcal{Q}}^{2}(\Psi(\upsilon))_{\tau}\right|+\left|\mathcal{F}_{\mathcal{P}}^{2}(\Psi(\upsilon))_{\tau}-\mathcal{F}_{\mathcal{Q}}^{2}(\Psi(\upsilon))_{\tau}\right|\right)=1-0$

$=S^{1}(\mathcal{P},\mathcal{Q})=1.$

3. Algorithm based on Intuitionistic Fuzzy Hypersoft Similarity Measures

In this section, we intend to propose an for the enhancement of ChatBot efficiency of customer support systems.

3.1 Algorithm

This algorithm integrates the principles of SMs into the development of a ChatBot system, enabling it to effectively handle uncertainty and vagueness in user interactions:

i. Represent user inquiries and the ChatBot's knowledge base as IFHSS in order to account for data ambiguity and uncertainty.
ii. *Receive natural language from user input* – Convert the user query into an IFHSM representation.
iii. *IFHSS similarity metrics* – Determine the degree of similarity, taking into account both membership and non-membership degrees, between user queries and stored information by using the stated measures.
iv. Utilizing the calculated similarity scores, compare the user query with already-existing knowledge base entries. Obtain the knowledge base entries or answers to the user's inquiry that are the most similar.
v. Provide a response taking into account the ambiguity and uncertainty present in IFHSSs, based on the knowledge base items that were collected. Adapt the answer according to

the user's query's degree of ambiguity and the amount of confidence in the matching process.

3.2 Comparison

To demonstrate the utility of the premeditated technique, we equate the achieved significance with some dominant methods (Table 3). According to Table 2, the suggested approach is expected to outperform several other hybrid set structures in terms of effectiveness, importance, superiority, and improvement.

Table 2
Comparison of proposed with existing studies

	Truthiness	*Falseness*	*Attributes*	*Sub-attributes*	*Distance SMs*
[6]	☑	☑	☑	☒	☒
[13]	☑	☑	☑	☒	☒
[20]	☑	☑	☑	☑	☒
[39]	☑	☑	☑	☒	☒
Proposed	☑	☑	☑	☑	☑

4. Conclusions

This research has explored the use of IFHSS in the assessment of similarity in ChatBot platforms. The first application regards the incorporation of IFHSS in the evaluation of similarity provisions a flexible and robust structure of addressing uncertainties and vagueness associated with human language conversations. Further, the application of intuitive elements enhances the responsiveness and versatility of ChatBots to diverse responses from users and differing circumstances.

In conclusion, the findings do indicate that IFHHS can be a valuable utility tool in stimulating the sophistication and performance of ChatBot platforms. Other research directions include further enhancements, scalability considerations, and test deployments to maximize the potential of this approach. Nevertheless, this research implies that the inclusion of IFHSS in SMs is an effective approach to enhancing ChatBots' intelligence and responsiveness, stimulating the growth of processing natural language.

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