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Research Paper

An Enhanced Framework for Efficient Point-of-Interest Recommendations in Recommender Systems

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ABSTRACT

Location-based recommender systems significantly enhance user experience in areas such as restaurant recommendations, recreational spaces, and urban services by utilizing spatial data and analyzing user behavior. This research proposes a novel framework to improve the accuracy and quality of recommendations, leveraging machine learning methods and neutrosophic multi-criteria decision modeling. The proposed model consists of three main stages: spatial data processing, recommender system optimization, and final recommendation ranking. Key features, including geographical proximity, user behavioral patterns, and social network data, have been identified to analyze locations more accurately. Clustering algorithms, such as the Imperialist Competitive Algorithm (ICA) and Fuzzy C-Means, are employed to identify geographically close clusters. Additionally, the neutrosophic VIKOR multi-criteria decision-making method is utilized for final ranking within each cluster. Evaluation results using datasets from Yelp, Foursquare, and Flickr indicate that the proposed model achieves higher accuracy compared to traditional methods. A comparison with baseline approaches, including Popularity Rank (PR), Classic Rank (CLR), and Frequent Rank (FR), demonstrates improved performance in terms of accuracy, mean absolute error, and user acceptance rate of recommendations. Furthermore, comparisons with other studies reveal that incorporating more comprehensive data, such as visit time and weather conditions, along with more detailed data analysis, enhances the quality of recommendations. Finally, a comparison of the proposed method with the CPRNS and MMPOI algorithms, both of which introduced a framework, shows that the implemented improvements achieve better performance in terms of Precision, Recall, and NDCG[2] metrics.

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1. Introduction

With the expansion of communication technologies and the increasing use of smart devices, recommender systems have become a key tool for enhancing user experiences in digital environments. Among them, Point-of-Interest (POI) recommendation systems in location-based social networks play a crucial role in guiding users to suitable locations. These systems provide personalized recommendations based on user check-in data, reviews, and textual features of POIs, facilitating the decision-making process. However, traditional recommendation methods still face challenges such as data sparsity, inaccurate ranking, and weak interpretability of recommendations [1].

A Point-of-Interest (POI) refers to a specific geographic location that holds value for users or information systems. These points may include public places such as restaurants, museums, parks, shopping centers, hotels, and other locations that users may wish to visit or obtain information about. In geographic information systems (GIS) and location-based services (LBS), POIs are used as data points that include information about location, categorization, user ratings, and other relevant attributes.

Location-based social networks (LBSNs) are a combination of social networks and location-based services that enable users to check in at their favorite places, share them, and interact with others. In these networks, users can rate specific locations, leave reviews, and share their experiences. The key features of geographic information systems include the following [2]:

Location Information: Users can specify their locations and search for Points-of-Interest.

Social Interaction: Users can exchange opinions, rate, and review visited places.

Personalized Recommendations: Suggestions for new places are provided based on user behavior patterns and others' reviews.

Behavioral Data: This includes check-ins, user reviews, and social interactions.

Common recommendation methods are primarily based on memory-based collaborative filtering and model-based collaborative filtering [3]. While memory-based methods heavily rely on user check-in data and struggle with data sparsity issues, model-based approaches often lack interpretability in explaining the provided rankings.

On the other hand, textual information such as geographic location, user interests, popularity, and social relationships plays a significant role in user decision-making. Research has shown that users tend to visit places near their previous check-ins or choose popular locations based on their friends' recommendations. Therefore, integrating these textual features with advanced decision-making models can enhance the accuracy and quality of recommendations.

To address the existing challenges and improve the accuracy of recommender systems, this research proposes a text-aware Point-of-Interest recommendation method based on neutrosophic sets. This approach transforms the Point-of-Interest recommendation problem into a multi-criteria decision-making context, enabling effective analysis and integration of textual features. Neutrosophic sets, which are an extension of fuzzy sets, can simultaneously represent information related to truth, falsehood, and uncertainty. This feature enhances the interpretability and justification of the provided recommendations, thereby improving the performance of the recommender system.

The selection of a Point-of-Interest by the user is influenced by several textual attributes. The challenge lies in accurately representing and effectively aggregating these textual attributes. This study performs Point-of-Interest recommendation from the user's perspective in a multi-criteria decision-making problem and proposes a text-aware Point-of-Interest recommendation method based on neutrosophic sets. Initially, geographic location is used as the basis for clustering to determine geographically close Points-of-Interest. Then, interest topics, popularity, and social relationships are effectively combined using neutrosophic sets, ultimately providing a list of recommended Points-of-Interest.

This paper presents a framework that, upon receiving input datasets, provides the best recommendations to users. This framework can be effectively generalized, and different criteria, methods, and combinations can be substituted to improve recommendations. The innovations proposed in this paper and their effectiveness in enhancing recommendations are also discussed.

Clustering of Points-of-Interest based on geographical location, number of visits to the location, weather conditions, season, traffic levels, and the user's mood has been used to increase accuracy [4].

Topics, popularity, and social relationships are combined using a multi-criteria neutrosophic set to create a higher quality of prioritization within each cluster.

The proposed innovations are presented in the form of a comprehensive framework, which, upon receiving available datasets, performs location prioritization with high accuracy.

This paper is structured as follows: Section 2 reviews the literature and examines related works. Section 3 presents the proposed method. In Section 4, the evaluation will be conducted under various scenarios to compare the proposed ideas with baseline methods. Section 5 concludes the paper and provides suggestions for future research.

2. Related Works

In Point-of-Interest recommendation, geographic location is considered a fundamental parameter for providing recommendations. Then, textual attribute parameters such as interest topics, popularity, and social relationships are taken into account to provide better recommendations and more accurate prioritization. Among the multiple criteria that influence user decision-making, the first consideration is the geographic location of the Point-of-Interest, which often affects users' decision-making behavior and represents the greatest difference between Point-of-Interest recommendations and traditional recommendations [5]. Users tend to visit a Point-of-Interest that is close to their previous location.

Users may be attracted to certain topics and reviews of a Point-of-Interest, leading to its acceptance. By considering the textual information related to the Point-of-Interest, the diversity of check-in data can be partially reduced. To better understand the LBSN pattern and improve its services, examining the available information and thematic features in the textual data is essential.

Typically, the personal decision to accept a hotel is strongly influenced by the public reputation of the Point-of-Interest, which can be interpreted as the popularity of the Point-of-Interest [6]. The popularity of a Point-of-Interest reflects the quality of the services and products it offers. Popularity has a significant impact on user acceptance behavior.

Friends often share similar interests, so utilizing users' social relationships can improve the accuracy and quality of recommendations related to Points-of-Interest in LBSNs. The impact of social relationships on Point-of-Interest recommendations has been studied in [7]. Typically, in this context, user similarity is evaluated based on the Points-of-Interest they have previously accepted, but the opinions of their friends are less considered in this process. However, the acceptance of a Point-of-Interest by friends can have different positive or negative impacts on users' decision-making. Therefore, simply considering the acceptance or non-acceptance of a Point-of-Interest by friends is not enough, and other influencing factors should also be examined.

To address the above issues and improve Point-of-Interest recommendations while preventing data sparsity, a text-aware Point-of-Interest recommendation method based on neutrosophic sets is proposed. This method transforms the Point-of-Interest recommendation problem into a multi-criteria decision-making process. Neutrosophic sets [7] are an extension of fuzzy sets and use information on membership degrees of truth, indeterminacy, and falsehood to represent fuzzy decision-making information, which can describe the nature of objective things in a precise and clear manner. This method is suitable for solving multi-criteria decision-making problems [8,9]. Neutrosophic logic provides a general framework for unifying many existing logics and extends vague logic (especially intuitive vague logic). The main idea of neutrosophic logic is to define each logical statement in a three-dimensional neutrosophic space, where each dimension represents the truth (T), falsehood (F), and uncertainty (I) of the statement.

The Point-of-Interest recommendation method belongs to a content-based solution, which is an essential tool for alleviating the problem of data sparsity. At the same time, the neutrosophic set-based method, which is based on collaborative filtering, can obtain the membership degree, non-membership degree, and uncertainty of each attribute of a Point-of-Interest, thereby clearly explaining the results of Point-of-Interest ranking.

Currently, personalized Point-of-Interest recommendations based on LBSNs have been widely studied. When users make check-ins in LBSNs, specific location information is required to be recorded on the server. Many current studies have considered some relevant attributes to improve the effectiveness of Point-of-Interest recommendations, such as geographic location [10,11], interests [12,13], popularity [14,15], social relationships [16,11], and so on. These attributes can enhance the impact of Point-of-Interest recommendations, but the improvement effect is limited. Ye et al. [2] proposed a linear integration framework by combining user preferences, social influences, and geographic influences, and designed a probabilistic prediction model for a specific user review of a Point-of-Interest. However, this method only considers the mentioned information and performs a linear combination. Zhang et al. [18] proposed a Point-of-Interest recommendation method called GeoSoCa, which uses the class-based, social, and geographic correlations between users and Points-of-Interest. This method models each type of information separately and then considers the product of the three scores as the final recommendation score. Additionally, the use of mature models to integrate multiple factors, such as common probabilistic models, is widespread. Liu et al. [18] presented a probabilistic latent factor model that considers user preferences, geographic influences, and user mobility during the recommendation process, using Poisson matrix factorization to obtain implicit feedback from user check-in data for better recommendations. However, due to the implicit nature of the variables, explaining the ranking results of Points-of-Interest to users is difficult. Recommendations that lack explainability cannot fully allow users to trust the results, which may lead users to think that the recommended items are merely commercial advertisements, thus reducing the credibility of the recommendation results. In comparison with model-based methods, the neutrosophic set-based method has a significant advantage in terms of explainability, which is inherently reflected in its structure, and the parameters have specific physical meanings that facilitate users' understanding of the outcomes.

Neutrosophic sets are widely used in image processing, pattern recognition, and medical diagnosis [19]. Neutrosophic sets are extensively used to solve MCDM

(Multi-Criteria Decision-Making) problems because they can represent fuzzy decision-making information in multiple dimensions. For example, Zhang et al. [20] used neutrosophic sets to represent user reviews in restaurants, which can simultaneously consider active, neutral, and passive information in online reviews, solving the fuzzy issue and the loss of uncertain information caused by using real numbers to represent textual reviews, providing decision support for users to choose a restaurant. Hua et al. [21] integrated cloud service evaluation data and users' application requirements, transforming them into neutrosophic sets to assess the uncertainty of the cloud environment and provide the most effective cloud services to users. Transforming multiple attributes affecting the selection of a Point-of-Interest into a neutrosophic set can provide an effective model for studying the Point-of-Interest recommendation problem. In [22], neutrosophic logic is also mentioned as a reasonable tool to find optimal replicas.

In [23], a new content-aware multi-faceted framework for Point-of-Interest recommendation, named MMPOI, is proposed. The approach addresses the data sparsity issue by using multi-faceted content information of Points-of-Interest from a new perspective. Specifically, MMPOI uses pre-trained models for interfaced transformation and employs a unified pre-trained model to extract features specific to each facet, effectively bridging the semantic gap between different facets. The paper suggests creating a multi-faceted path flow graph that combines the multi-faceted semantic structure with the entry sequence records. Furthermore, an adaptive multi-task transformer is designed to model the multi-faceted movement patterns of users and integrate them for the next Point-of-Interest recommendation tasks. Extensive experiments on four real-world datasets demonstrate that MMPOI outperforms advanced recommendation methods.

The proposed MMPOI framework consists of four main components. A pre-trained Image2Text model is used to convert images of locations into textual descriptions. Then, a pre-trained language model is employed to extract features specific to each modality from each type of data. The specific features of different modalities of locations are combined with user location sequence logs, and a multi-modal path flow graph is created to learn location representations. A geographic path flow graph is created to model the spatial relationships between locations. Check-in representations from geographical locations, multimedia content of places, user preferences, and temporal patterns are learned. An adaptive multi-task transformer is proposed to model user movement patterns and provide location recommendations.

Recommendation of Points-of-Interest has become one of the main functionalities of location-based services. Unlike traditional item recommendation systems (such as for movies or books), location-based recommendation systems have unique features such as geographic influences, complex movement patterns, and a balance between users' local and global preferences [24]. Previous research in the field of location-based recommendation systems has largely focused on integrating deep learning models such as convolutional neural networks, recurrent neural networks, and attention mechanism-based architectures, which have demonstrated their effectiveness in processing spatiotemporal data in location recommendation systems. In recent years, with the emergence of large language models, location-based recommendation systems have entered promising research paths. This paper first discusses the features and advanced approaches of location-based recommendation systems and then introduces new research directions by integrating large language models.

In [25], a comparison was made between traditional AI-based recommendation systems and generative AI-based recommendation systems. In total, fifty-two published papers from the period of 2019 to February 2024 were selected from six reputable online libraries. To gain a more comprehensive understanding of the selected studies, the techniques, models, datasets, and evaluation metrics used were examined. The systematic review indicates that generative AI models, such as Generative Adversarial Networks (GANs), Variational Autoencoders (VAEs), and Autoencoders, have been widely used in recommendation systems and perform better than traditional AI techniques.

With the rapid development of mobile communication technology, there is an increasing demand for high-quality Point-of-Interest (POI) recommendations. The POIs visited by users only make up a very small fraction of the total, which makes the traditional POI recommendation method vulnerable to data sparsity and lacks a clear and effective explanation for the ranking results. The selection of POIs by users is influenced by various contextual features. There is an inherent challenge in presenting and efficiently aggregating textual information. [26] transforms POI recommendation into a multi-feature decision-making problem based on Neutrosophic Sets (NS), which is suitable for representing fuzzy decision information. This paper proposes an integrated framework of contextual information. In the first step, a multi-feature NS transformation model for POIs is suggested, including the NS model for single-dimensional features and the NS model for multi-dimensional features. Then, through the aggregation of multiple NS features, the POIs that best match the user's preferences are recommended. Finally, empirical results based on the Yelp dataset show that the proposed strategy outperforms previous methods in terms of NDCG, accuracy, and recall rate.

3. Proposed Method

In the proposed method, as shown in Figure 1, a framework is suggested that ultimately provides the necessary recommendations using input data. The information extracted from the datasets is organized in files placed together. In the Point-of-Interest recommendation based on context, criteria such as the geographical coordinates (latitude and longitude), subject, popularity, and social relationships are considered. To make cluster identification based on geographical coordinates more accurate, criteria such as the number of visits, weather conditions, time of visit, visitor's mood (emoji), season, and traffic are also examined, and the Points-of-Interest are clustered. Other criteria are sorted based on neutrosophic logic, and after comparison within the cluster, the priorities are determined based on the highest probability. Our research shows that, among various features influencing user decision-making, geographic location is the most important factor, which is one of the biggest differences between location-based recommendations and traditional recommendations [26]. Users tend to visit a Point-of-Interest that is close to their previous check-in location.

A person's decision to check-in at a Point-of-Interest is usually significantly influenced by its public reputation, which can be described as the popularity of the Point-of-Interest [26]. The popularity of a Point-of-Interest reflects the quality of services and products offered by it. Popularity significantly affects users' check-in behaviors.

Friends are more likely to share common tastes than strangers, and utilizing users' social relationships can improve the quality of Point-of-Interest recommendations in location-based social network systems. In such systems, similarity is often determined by whether the check-ins at a Point-of-Interest match with others, without considering the reviews from the user's friends about the Point-of-Interest. When a user's friends check-in at a Point-of-Interest, they may provide either positive or negative feedback, which can have a very different impact on the user. It is not sufficient to only examine whether a friend has checked in or not.

Suppose there are m candidate Points-of-Interest denoted as l1, l2, · · ·, lm−1, lm. It is necessary to extract geographic location information, membership in topic clusters, review information, and social relationships of the candidates from the rich data of location-based social networks. The second and third layers of the Point-of-Interest recommendation based on the neutrosophic set are shown in Figure 1.

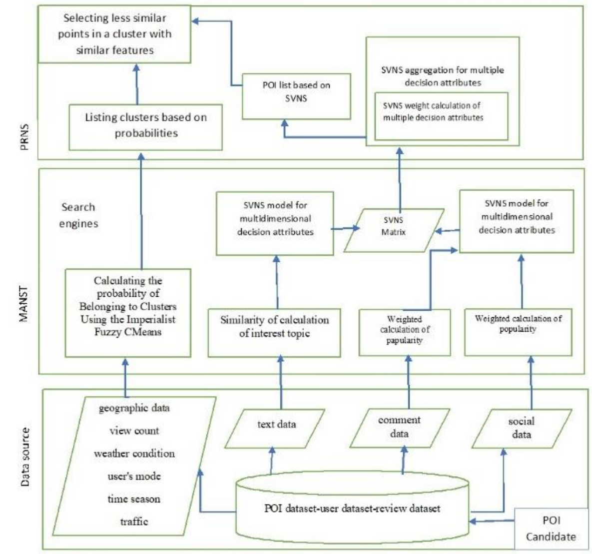

Fig1. Proposed Recommendation System Framework for Providing Recommendations at Points-of-Interest

The second layer of the model involves the multi-feature neutrosophic set transformation and neutrosophic set-based Point-of-Interest recommendation. In this layer, SVNS is introduced as the key concept. Before presenting this concept, however, a precise definition of the neutrosophic set is necessary.

Definition 1

Neutrosophic Set (NS): Suppose X is a space of subjects. The general components in X are denoted by x. A neutrosophic set in X is denoted by A, and it is determined by the truth membership function TA(X), the uncertainty membership function IA(X), and the false membership function FA(X). These three functions are subsets of the standard or non-standard range [0−,1+], i.e., TA(x):X→[0−,1+], FA(x):X→[0−,1+] and IA(x):X→[0−,1+]. There are no restrictions on the sum of IA(X), FA(X), and TA(X); therefore, 0−<TA(x)+IA(x)+FA(x)<1+. Neutrosophic is based on the philosophical principle which makes its processing challenging for practical applications.

Definition 2

Single-Valued Neutrosophic Set (SVNS): Suppose X is a space of subjects with general components in X denoted by x. A is an SVNS, which is a subclass of NS, and is defined by relation (1):

$$A = \{T_A(x), I_A(x), F_A(x) \mid x \in X\} \qquad (1)$$

where $T_A(x): X \to [0,1]$, $I_A(x): X \to [0,1]$, and $F_A(x): X \to [0,1]$, and $0 \leq T_A(x) + I_A(x) + F_A(x) \leq 3$.

For simplicity, we use a = {T, I, F}to represent an element in the SVNS, which is called a Single-Valued Neutrosophic Number (SVNN).

Definition 3

Basic Computational Rules of Single-Valued Neutrosophic Numbers: Suppose that a1= $\{T_1, I_1, F_1\}$ and

$a_2 = \{T_2, I_2, F_2\}$ are two single-valued neutrosophic numbers; then the computational rules are defined as (2).

$$\lambda a_1 = \langle 1-(1-T_1)^{\lambda}, (I_1)^{\lambda}, (F_1)^{\lambda}\rangle; \lambda > 0 \quad (2)$$

$$a_1^{\lambda} = \langle (T_1)^{\lambda}, 1-(1-I_1)^{\lambda}, 1-(1-F_1)^{\lambda}\rangle; \lambda > 0$$

$$a_1 \oplus a_2 = \langle T_1 + T_2 - T_1 \cdot T_2, I_1 \cdot I_2, F_1 \cdot F_2\rangle$$

$$a_1 \otimes a_2 = \langle T_1 \cdot T_2, I_1 + I_2 - I_1 \cdot I_2, F_1 + F_2 - F_1 \cdot F_2\rangle$$

The complement of a1 is equal to $a_1^c = \langle F_1, 1-I_1, T_1\rangle$.

Definition 4

Euclidean Distance of Two Single-Valued Neutrosophic Numbers: Suppose that $a_1 = \{T_1, I_1, F_1\}$ and $a_2 = \{T_2, I_2, F_2\}$ are two SVNNs, then the Euclidean distance between a_1 and a_2 is determined by Equation (3).

$$d(a_1, a_2) = \sqrt{\frac{|T_1 - T_2|^2 + |I_1 - I_2|^2 + |F_1 - F_2|^2}{3}} \quad (3)$$

Definition 5

Weighted Average Operator of Single-Valued Neutrosophic Sets: Suppose that $A_i = \langle T_i, I_i, F_i\rangle$ (i=1, 2..., n) is a set of SVNSs. The weighted average operator of SVNSs (SVNSWA) is defined as in Equation (4).

$$\text{SVNSWA } A_{\omega}(A_1, A_2, \cdots, A_n) = \omega_1 \cdot A_1 \oplus \omega_2 \cdot A_2 \oplus \cdots \oplus \omega_n \cdot A_n = \sum_{i=1}^{n} \omega_i A_i \quad (4)$$

Where ω= (ω1, ω2, …, ωn) is the weight vector of A_1, and $\sum_{i=1}^{n} \omega_i = 1$.

Theorem 1. Suppose that $A_i = \langle T_i, I_i, F_i\rangle$ (i=1, 2..., n) is a set of SVNSs. Then, their aggregated result using the SVNSWA operator is also an SVNS, and

$$\begin{aligned}\text{SVNSWA } A_{\omega}(A_1, A_2, \cdots, A_n) &= \omega_1 \cdot A_1 \oplus \omega_2 \cdot A_2 \oplus \cdots \oplus \omega_n \cdot A_n \\ &= \left\langle 1 - \prod_{i=1}^{n} (1-T_i)^{\omega_i}, \prod_{i=1}^{n} (I_i)^{\omega_i}, \prod_{i=1}^{n} (F_i)^{\omega_i} \right\rangle\end{aligned} \quad (5)$$

Where ω= (ω1, ω2, …, ωn) is the weight vector of Ai, and $\sum_{i=1}^{n} \omega_i = 1$.

For contextual information with different data structures, the multi-attribute neutrosophic set transformation model utilizes similarity-based methods or text analysis-based methods, such as sentiment analysis, to convert diverse contextual data into neutrosophic sets. This approach enables a better measurement of user preferences for a specific attribute. The single-valued, one-dimensional neutrosophic set transformation model based on similarity is designed for multi-criteria decision-making, focusing on the similarity between alternatives and an ideal criterion. The one-dimensional transformation processes each criterion separately rather than considering a combination of criteria.

The concept of similarity measure in this model involves calculating the similarity of decision-making options to an ideal value. To compute the similarity between the options and the ideal value, cosine similarity or other similarity measures such as Jaccard are used. A common formula for measuring the similarity between two SVNNs, for example, option **A** and the ideal option **I**, is given by Equation (6).

$$Sim(A, I) = \frac{T_A \times T_I + (1-F_A) \times (1-F_I) + (1-I_A) \times (1-I_I)}{\sqrt{T_I^2 + (1-F_I)^2 + (1-I_I)^2} \times \sqrt{T_A^2 + (1-F_A)^2 + (1-I_A)^2}} \quad (6)$$

The general steps of the SVNS transformation model in multi-criteria decision-making include determining the criteria and options. First, the decision-making criteria are identified. The information is represented using SVNS sets, where each option is assigned values (T, F, I) based on different criteria. The next step involves converting the SVNS data into a suitable numerical form for better analysis. Then, the criteria are normalized and weighted according to their importance. Finally, the decision-making options are ranked, and the best option is selected. Equation (7) illustrates the functionality of this process.

$$S = T - F - I \quad (7)$$

Creating a single-valued neutrosophic set (SVNS) matrix is not a complex task. The two-box SVNS models—one-dimensional decision-making based on similarity to the ideal state and multi-dimensional decision-making—each generate a matrix where the rows represent Points-of-Interest, and the columns consist of the T, F, and I value derived from the criteria. These values are aggregated to ultimately form a single matrix. Equation (8) illustrates the structure of this matrix.

$$\begin{bmatrix} (T_{11}, F_{11}, I_{11}) & \cdots & (T_{1n}, F_{1n}, I_{1n}) \\ \vdots & \ddots & \vdots \\ (T_{m1}, F_{m1}, I_{m1}) & \cdots & (T_{mn}, F_{mn}, I_{mn}) \end{bmatrix} \quad (8)$$

In the third layer of the Point-of-Interest recommendation model, the importance of each contextual feature is measured based on the neutrosophic set, effectively integrating the features to identify the Points-of-Interest that best match the user's needs. Based on the neutrosophic set matrix obtained through the multi-attribute neutrosophic set transformation model, the model calculates the weight of each feature and aggregates the neutrosophic sets of multiple decision-making attributes for each Point-of-Interest. Then, it ranks them according to the neutrosophic numbers associated with each Point-of-Interest. Finally, the user receives a recommended list of Points-of-Interest in the form of $lr_1, lr_2, \ldots, lr_m$. The highest-ranked Point-of-Interest in the list has the best match with the user's preferences and is more likely to be selected compared to lower-ranked Points-of-Interest. In this study, the appropriate number of clusters is first determined, and user interests are clustered in a fuzzy system, where each interest may belong to one or multiple clusters with a certain probability due to the fuzzy nature. In the next step, using the neutrosophic VIKOR method, the interests within each cluster are ranked, and the priority of Points-of-Interest is extracted.

The key point utilized in this dissertation is that if Points-of-Interest within a cluster are recommended based on the user's ranked preferences, similarity will be the primary criterion. As a result, the first, second, and third recommended locations will have the highest similarity to each other, leading the user to visit places with similar features. However, for a tourist, the best experience involves visiting locations that, while belonging to the same general category of interest, offer diverse features. This approach helps optimize time efficiency. In the final box of our proposed framework, this issue is addressed by ensuring that diversity is maintained alongside similarity.

3-1. Better Clustering with Increased Membership Using the Imperialist and Fuzzy C-Means Method

The extraction and preprocessing of data for a location-based travel recommendation system involve creating graphs for learning location representations and modeling geographical relationships. The required data is sourced from platforms such as Flickr and includes information on location, popularity, weather conditions, visit time, traffic, and the user's emotional state. The proposed algorithm utilizes imperialist competition to automatically cluster locations. By defining criteria such as cohesion and separation, the algorithm identifies the optimal number of clusters and optimizes the clustering process [27]. Next, the Fuzzy C-Means clustering method is applied to allow locations to flexibly belong to multiple clusters. This approach helps mitigate the issue of data sparsity and enhances the accuracy of recommendations. The objective function in this algorithm aims to minimize the distance between data points and cluster centers, while the membership value of each data point in a cluster is assigned a numerical value between zero and one. This process continues until the cluster centers stabilize, ultimately producing the final clusters to improve the performance of the recommendation system [27].

In summary, the Reasons for Using the Imperialist Competitive Algorithm (ICA) for Initial Clustering are:

A. Optimization Performance: The Imperialist Competitive Algorithm is an evolutionary algorithm based on the idea of imperialistic competition, which mimics the social and political behavior of empires. This algorithm has shown remarkable performance in solving optimization problems, especially in complex, nonlinear, and multi-dimensional spaces. Its ability to effectively navigate the solution space makes it a suitable choice for accurately identifying initial clusters of geographic locations or user preferences.

B. Efficient Cluster Formation: ICA's core mechanism involves competition among "empires" (clusters) which allows it to efficiently discover optimal and relevant clusters. By using a population-based approach, ICA can explore multiple potential solutions simultaneously, resulting in a more thorough and effective formation of clusters that genuinely reflect user behavior and spatial relationships.

C. Ability to Handle Unstructured Data: Recommendation systems often deal with unstructured and high-dimensional data, such as user-generated content, social interactions, and spatial data. The ICA is designed to handle such complexities, making it well-suited for clustering geographic data and behavioral patterns that might not fit neatly into traditional clustering methods.

D. Adaptability to Dynamic Conditions: The behavior of users and environmental conditions can change over time, necessitating a flexible clustering approach. ICA can adapt to fluctuations in data patterns, allowing it to update and refine clusters as new data becomes available. This adaptability ensures that the system remains relevant and effective in providing high-quality recommendations based on the most current user interactions.

E. Automatic Determination of Cluster Numbers: One of the significant advantages of ICA over traditional clustering algorithms like K-Means is its ability to automatically determine the number of clusters. Traditional algorithms often require the number of clusters to be predefined, which can lead to suboptimal clustering if the specified number does not accurately reflect the data structure. ICA, on the other hand, dynamically adjusts the number of clusters based on the underlying data, leading to more accurate and meaningful clustering.

F. Integration of Multiple Criteria: ICA facilitates the simultaneous optimization of multiple criteria, which is essential for clustering in recommendation systems. For instance, it can consider various factors such as geographic proximity, user preferences, ratings, and social influence when forming clusters. This multi-criteria optimization ensures that the resultant clusters are not only based on distance but also on the contextual relevance of the data.

G. Competitive Exploration: The imperialistic nature of ICA fosters a competitive environment where strong solutions (empires) can dominate and influence weaker ones. This competition leads to the exploration of diverse solutions, reducing the likelihood of convergence to local minima and enhancing the robustness of the clustering process.

H. Improved Quality of Recommendations: By leveraging the clustering capabilities of ICA, a recommendation system can improve the quality of recommendations made to users. Clusters formed through ICA will be more representative of user behavior and location characteristics, thus yielding more personalized and context-aware recommendations.

After the cluster centers and the number of clusters are determined by the Imperialist Competitive Algorithm, these centers are used as the initial centers for the Fuzzy C-Means algorithm. Then, the Fuzzy C-Means algorithm is executed, ultimately yielding the clustered locations. Next, specific clusters are assigned to each user. For example, a user may have visited locations belonging to clusters 1, 2, and 4. Based on these clusters, recommendations are provided to the user with certain probabilities.

In summary reasons for using Fuzzy C-Means Clustering After ICA:

A. Refinement of Cluster Centers: After the initial cluster centers and the number of clusters are determined by the ICA, the Fuzzy C-Means algorithm is employed to refine these cluster centers further. FCM operates on the principle of fuzzy membership, allowing each data point to belong to multiple clusters to varying degrees. This characteristic is particularly valuable in applications like recommendation systems, where user preferences and behaviors can be complex and not strictly belong to a single category.

B. Handling Fuzziness and Ambiguity: In real-world scenarios, user behaviors exhibit a high degree of fuzziness. For instance, a user might enjoy both restaurants and recreational spaces, which may belong to different clusters. FCM's ability to assign partial membership values to data points enables the system to capture the nuanced nature of user preferences more effectively than hard clustering methods, such as those traditionally used in other algorithms.

C. Enhanced Flexibility: FCM allows users and items to be members of multiple clusters based on degree rather than by strict assignment. This flexibility helps in creating a more personalized recommendation set, as recommendations can be drawn from several overlapping clusters. For example, if a user has shown interest in restaurants (Cluster 1) along with nearby parks (Cluster 2), FCM will allow both clusters' influence on the recommendations.

D. Improvement in Recommendation Quality: By using Fuzzy C-Means following ICA, the system can provide more relevant and diverse recommendations. As each user can be associated with multiple clusters based on their past interactions and behaviors, the recommendation engine can suggest places that align more closely with the user's preferences. For instance, if a user frequently visits locations from multiple clusters, the system can recommend a mix of those locations, increasing the likelihood of user satisfaction.

E. Capability to Model Uncertainty: FCM is particularly adept at dealing with uncertainty in data. In recommendation systems, users often have diverse preferences that cannot be easily categorized. By allowing degrees of membership, FCM provides a mechanism to model this uncertainty, thereby enhancing the robustness of the recommendations made.

F. Iterative Optimization: Fuzzy C-Means is an iterative algorithm that refines the cluster centers while adjusting the membership values based on the current classification of data points. This iterative optimization helps in converging towards a more accurate representation of the clusters and provides a more robust clustering solution that reflects the underlying patterns in the data.

G. Combination of Strengths: The combined use of ICA and Fuzzy C-Means leverages the strengths of both algorithms. While ICA efficiently determines initial cluster centers based on competitive imperialist paradigms, FCM can refine these centers to account for the complex and fuzzy nature of user preferences. This synergy results in a more effective clustering approach for location-based recommendation systems.

H. Empirical Validation: In practice, empirical evidence often shows that the combination of ICA and FCM yields improved performance in terms of accuracy and user satisfaction in recommendations. By utilizing FCM after ICA, the recommendation system can better harness the spatial and behavioral data provided, leading to more accurate clustering and, consequently, better recommendations.

3-2. One-Dimensional SVNS Model Based on Similarity

The SVNS transformation model for analyzing the multidimensional features of Points-of-Interest consists of two main components: popularity and social relationships. Popularity of a location depends on its public reputation and is assessed through user evaluations. In the social relationships section, the influence of friends' opinions on users is examined. For sentiment analysis of user reviews, lexicon-based models such as VADER and deep learning models like BERT are used. VADER is suitable for informal texts but has limited accuracy, whereas BERT, with bidirectional processing and transfer learning, performs better in sentiment analysis. The BERT method is used here. This model classifies reviews into positive, negative, and neutral and calculates the values T, I, F.

In the transformation of multidimensional features to SVNS, the weight of each opinion is determined based on various factors such as the publication time (for popularity) and behavioral similarity and social familiarity (for social relationships). The Social Influence Index (SI) is calculated by combining similarity and popularity among friends, and the weight of friends' opinions is considered. Finally, using the SVNSWA operator, the final values of popularity and social relationships are extracted and stored in the SVNS matrix.

3-3. SVNS Matrix and POI

The output of both previous sections consists of results that show the T, F, I value for each Point-of-Interest (POI). In practice, the output of the second layer is a matrix where the rows represent the Points-of-Interest and the columns represent the neutrosophic values obtained for the criteria of subject, popularity, and social relationships. Equation (3) illustrates the structure of this matrix. In other words, a matrix is created with the number of Points-of-Interest in the dataset for the rows and three columns for the criteria, with each entry containing the three components T, F, and I. In the third layer, sorting and prioritization must be performed. The POI matrix is a matrix where the rows represent the Points-of-Interest and the columns represent the criteria. The values in the matrix are regular data, not neutrosophic. These values are used to determine the weights for the VIKOR algorithm and as input for the CRITIC[1] algorithm.

3-4. Prioritizing Points-of-Interest Using the VIKOR Method

The VIKOR method is multi-criteria decision-making (MCDM) technique used to solve problems with conflicting criteria. This method provides a compromise solution that balances different criteria. In the problem under consideration, criteria such as topic of interest, popularity, and social relationships may influence users' decisions when selecting a location, but they are not necessarily aligned. VIKOR ranks the options by calculating the distance of each option from the ideal and anti-ideal solutions, and determines the best option based on the Q index. This index is a combination of two values, S and R, which represent the distance from the ideal and anti-ideal solutions, respectively. The parameter v in this model specifies which of these distances the decision-making process should rely on more.

Here's a detailed explanation of why the neutrosophic VIKOR method and CRITIC are utilized after the ICA and Fuzzy C-Means clustering in a recommendation system:

A. Complex Decision-Making Environment:

Recommendation systems often operate in environments where decisions need to be made based on multiple, often conflicting criteria. After clustering the data using ICA and Fuzzy C-Means, the next logical step is to evaluate and rank the recommendations based on various factors such as user preferences, environmental conditions, and location characteristics. Neutrosophic VIKOR is particularly well-suited for this purpose as it provides a framework for multi-criteria decision-making (MCDM) under uncertainty.

B. Handling Uncertainty and Imprecision: Neutrosophic logic extends traditional fuzzy logic by allowing for the representation of truth, falsehood, and indeterminacy degrees, making it ideal for environments where information is incomplete or uncertain. In the context of recommendation systems, user preferences and behaviors can often be ambiguous. The neutrosophic VIKOR method can accommodate this uncertainty, enabling more robust decision-making in the ranking process.

C. Comprehensive Ranking of Alternatives: The VIKOR method is designed to identify a compromise solution among a set of alternatives, which is important when dealing with multiple clusters generated by Fuzzy C-Means. After clustering, there are usually multiple recommendations available for users. VIKOR helps to rank these alternatives based on their overall desirability and performance across multiple criteria, ensuring that users receive well-rounded recommendations that reflect their preferences effectively.

D. Utilization of CRITIC for Criterion Weighting: Before applying the VIKOR method, the CRITIC (Criteria Importance Through Intercriteria Correlation) method is employed to determine the weights of different criteria involved in the decision-making process. CRITIC evaluates the importance of each criterion based on how well it differentiates between alternatives (in this case, recommended locations) and its correlation with other criteria. This ensures that the most relevant factors have a proportionate influence on the final ranking of recommendations, leading to more informed decisions.

E. Integration of Diverse Criteria: By using both neutrosophic VIKOR and CRITIC, the recommendation system can effectively integrate different types of criteria, such as user ratings, proximity to the user's location, and contextual factors (e.g., time of day, weather conditions). This integration allows for a holistic assessment of each recommended alternative, ensuring that users receive recommendations that are not only popular but also contextually relevant and personalized.

F. Improved User Satisfaction: The ultimate goal of a recommendation system is to enhance user satisfaction. By utilizing neutrosophic VIKOR for ranking and CRITIC for weighting, the system is better equipped to deliver recommendations that align closely with user preferences. This tailored approach reduces the likelihood of irrelevant suggestions and improves the effectiveness of the recommendations provided.

F. Iterative Improvement through Feedback: The neutrosophic VIKOR method allows for an iterative process where user feedback can be integrated into the ranking mechanism. This feedback can help fine-tune the criteria and their weights, continuously improving the recommendation accuracy over time. The system can adapt to changing user preferences, further enhancing user experience.

G. Empirical Validation and Performance Metrics: Lastly, empirical studies have demonstrated that combining MCDM methods like neutrosophic VIKOR and CRITIC with the earlier clustering techniques yields better performance metrics—such as higher accuracy, precision, and user satisfaction—in recommendation systems. This combination provides a competitive advantage over traditional methods by incorporating a more sophisticated decision-making framework.

3-5. Neutrosophic Multi-Criteria Decision-Making Model Based on Frequent Patterns with Adjusted Weights

The neutrosophic VIKOR method in multi-criteria decision-making ranks Points-of-Interest based on their proximity to the positive ideal solution and distance from the negative ideal solution. However, a challenge in this method is the weighting of criteria. To determine the weights of the criteria, the CRITIC method is used, which is an objective, data-driven technique. This method determines the weights of criteria based on two characteristics: the diversity of values (higher standard deviation indicates more information) and the independence of criteria (lower correlation with other criteria).

Initially, a decision matrix containing the values of the criteria is created, then the standard deviation and correlation coefficient of the criteria are calculated. Finally, the weight of each criterion is derived from a combination of these values and normalized. This method has weaknesses such as not accounting for the subjective value of criteria and being sensitive to data scaling. However, in this research, these challenges do not significantly impact the results.

3-6. Sorted List of Points-of-Interest in Each Cluster

The final step and result of the proposed framework is a list of Points-of-Interest that are sorted within a cluster and recommended. This section can provide recommendations that align with the importance of the Point-of-Interest and the user's needs.

4.Evaluation

4-1. Comparison of Cluster Quality of the Proposed Method

In this section, the proposed method is compared with some existing methods in travel recommendation systems with Points-of-Interest to determine its position in the current research in this field. Initially, the proposed method is compared with a series of standard baseline methods that are commonly used in many articles to measure accuracy, such as Popularity Rank (PR) [29], Classic Rank (CLR) [29], and Frequent Rank (FR) [30]. It is important to note that all of these baseline methods have been implemented and evaluated using the dataset presented in this article. Additionally, several existing studies in the field of travel recommendation systems are measured with parameters related to cluster quality, such as accuracy, mean absolute accuracy, and mean absolute error [27].

4-2. Evaluation of Multi-Criteria Decision-Making Methods for Ranking Points-of-Interest

As shown in Figure 1, the proposed framework consists of several components, each of which has been individually examined and analyzed. Various tools have been used to address the challenges of each section, and the results have been compared, with the idea of reaching the best result reported as the main solution.

As explained in detail in Section 3, the criteria of topic, popularity, and the social relationships of user reviews about a Point-of-Interest are processed into a ranking within a predefined cluster. In some ranking methods, several options may have very similar values, and the method may not be able to create a clear distinction between them. This usually happens when the options do not differ much in terms of certain criteria. When the method used only considers distance, slight differences between the options will not be identified. The VIKOR method solves this problem by using two separate criteria to differentiate the options: 1. Satisfaction Index (Si), which measures the total distance of an option from the ideal value (a summative approach), and 2. Worst Performance Index (Ri), which measures the largest distance of a criterion from the ideal value for each option (a maximization approach). While methods like TOPSIS base decisions only on the overall distance of an option from the ideal, VIKOR considers that an option might have a significant weakness in a specific criterion, even if it performs well overall. This allows VIKOR to better distinguish between very close options.

As mentioned, 125 different locations in Paris, with all fields available and each location having 20 different reviews, were extracted from Flickr. The previous analysis revealed that the best clustering method was dividing the data into three distinct clusters. In this study, the TOPSIS, VIKOR, and SAW methods were compared.

4-2-1. Average and Standard Deviation of Ranking

Table 1 shows the average and standard deviation of rankings using three different multi-criteria decision-making methods.

If the dataset extracted from Flickr, which includes 2500 individuals, has 3 clusters, as per the clustering method described in the previous section, and the average ranking for the VIKOR Neutrosophic method is 400, this indicates that the distribution of rankings is relatively symmetrical. According to the table, it can be observed that in 10 executions of the clustering algorithm, the average rank for the VIKOR Neutrosophic method is 378. In comparison, the TOPSIS Neutrosophic method has an average rank of 292, and the SAW Neutrosophic method has an average rank of 281. The VIKOR method shows less bias towards higher or lower rankings. The average score of 378 for VIKOR Neutrosophic indicates that the rankings are generally evenly distributed across the entire range for each cluster (1 to 800).

If the average rank is much lower than 400 (for example, 281), it suggests that the method tends to place more individuals in higher (lower) ranks and may indicate a bias towards top choices. If the average rank is much higher than 400 (for example, 600), it suggests that the method tends to place more individuals in weaker (higher) ranks, reflecting less differentiation between top and lower options. Therefore, an average rank close to 400 indicates that VIKOR creates a balanced distribution and avoids bias in the ranking process. In ranking these Points-of-Interest, places where the score and rank are equal cause the overall score to be shifted in the end.

Table 1. Average rank in each cluster for the VIKOR neutrosophic method compared to other methods in the Flickr and Foursquare datasets

Method	Average rank (number of clusters = 3, average number per cluster = 812)	Standard deviation in each cluster
SAW Neutrosophic	281	211
TOPSIS Neutrosophic	292	182
VIKOR Neutrosophic	378	163

The standard deviation plays an important role in determining the superiority of the VIKOR Neutrosophic method because it indicates the extent of the dispersion in the rankings. If a method has a very high standard deviation, it means that its rankings have large fluctuations, evaluating some options very high and others very low, which may indicate instability in the method. On the other hand, if the standard deviation is very low, the method may not create enough differentiation between options and may place the rankings too close to each other, which can reduce the method's effectiveness. In Table 1, the VIKOR Neutrosophic method shows lower standard deviation values and better performance, while having a higher average ranking, thus demonstrating better discriminability. An ideal method should strike a balance between these two factors, meaning it should have a moderate standard deviation to create appropriate differentiation between close options and avoid extreme fluctuations in the rankings. Therefore, comparing standard deviations in different methods can serve as a criterion for evaluating their accuracy, stability, and discriminative capabilities. Thus, VIKOR creates better differentiation between close options and, compared to other methods, has fewer duplicate rankings. A lower correlation with other methods indicates ranking differentiation.

Table 2. Average Rank in Each Cluster for the VIKOR Neutrosophic Method Compared to Other Methods in the Yelp Dataset

method	Average rank (number of clusters = 3, average number per cluster = 51658)	Standard deviation in each cluster
SAW Neutrosophic	18620	10904
TOPSIS Neutrosophic	22786	12954
VIKOR Neutrosophic	26457	11273

In Table 2, the new conditions for the Yelp dataset are specified. The results still favor VIKOR, and the results and analysis align with Table 1. Given that the overall evaluation of the framework is based on Yelp, an effort has been made to consider a large number of data points to both increase accuracy and remain consistent with previous work.

4-2-2. Evaluation of the Proposed Framework

In the performance evaluation of the proposed framework, the metrics Recall, Precision, NDCG, and HR are used. The evaluation parameter Precision is obtained from the following formula. Precision is the ratio of the number of interested locations reviewed by the user among the N top recommended locations to the total number N. The precision of the recommendation results is defined by equation 9.

$$precsion@N = \frac{|P(u_i) \cap R(u_i)|}{N} \qquad (9)$$

Here, P(ui) is the recommended set for user ui based on the training set, and R(ui) is the set of Points-of-Interest (POI) that user ui has visited in the test set. The Recall rate is the ratio of the number of interested locations that users have reviewed among the N top recommended locations to the total number of interested locations that users have reviewed in the test set. The Recall rate of the recommendation results is defined by equation 10.

$$Recall@N = \frac{||p(u_i) \cap R(u_i)||}{R(u_i)} \qquad (10)$$

In this paper, the ranking quality index commonly used, NDCG, is employed as the evaluation metric, which is defined in equation 11.

$$NDCG@N = \frac{DCG@N}{IDCG@N} \qquad (11)$$

Here, N is the length of the recommendation list, and DCG@N is equal to $\sum_{j=1}^{N} \frac{2^{rel_j}-1}{log_2(r_j+1)}$, and IDCG@N is the value of DCG@N when the recommended items are ideally ranked. rel_j is the graded relevance at position r_j, which is defined in different recommendation scenarios . In the case of Point-of-Interest recommendations, based on rankings, it can be assumed that $rel_j = \{1, 2, 3, 4, 5\}$. NDCG is a value between 0 and 1. The larger the value, the better the ranking performance.

HR@N, as seen in equation 12, is a metric commonly used in location-based recommendation systems to check whether the user's next location is present in the top N recommended list or not.

$$HR@N = \frac{1}{|U|} \sum_{u \in U} (POI_u \in R_u^N) \qquad (12)$$

Where U is the set of users. POI_u is the actual location that user u later visited. R_u^N is the top N recommended list for user u. To validate the effectiveness of the proposed VIKOR Neutrosophic method in ranking contextual features in this thesis, the topics of interest, popularity, and social relationships are examined in relation to the recommendation results in each experiment. Also, in another study, instead of the CRITIC method, equal weights are used for the criteria in the VIKOR method. These experiments are simplified versions of our proposed model. Additionally, the CPRNS method, which operates based on aggregating the

SVNS values, is compared with the proposed method. By showing performance improvement over this method, it is demonstrated that the proposed method performs very well.

In these methods, VIKORNS-WI[3] does not consider information related to topics of interest. VIKORNS-WP[4] does not consider information related to popularity. VIKORNS-WS[5] does not consider information related to social relationships. VIKORNS-WPW[6] uses the Vikor Neutrosophic framework but does not assign personalized weights for the four main features; instead, it assigns equal weights to all features.

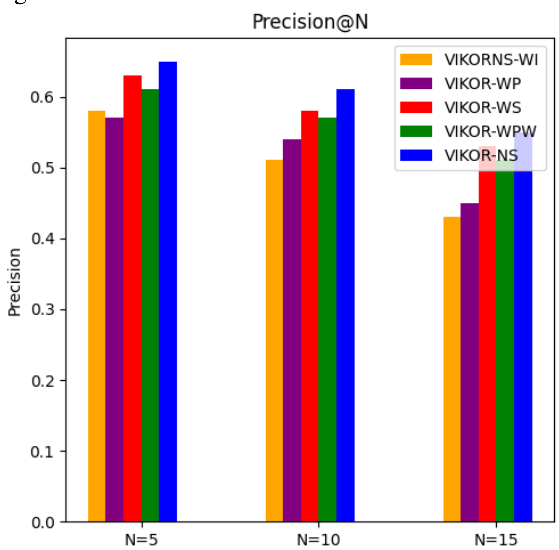

Fig 2. The chart related to Precision for the number of listed Points-of-Interest

An analysis of Figure 2 shows the lower performance of VIKORNS-WI, represented by the orange chart, which does not consider the users' topic-related information. Since in many scenarios, users' topic preferences significantly affect the accuracy of recommendation systems, ignoring this information has led to lower performance for this method. This limitation is particularly evident at lower values of N, such as N=5, where users require more accurate and relevant responses. The VIKOR-WP method, shown in the purple chart, ignores popularity-related information. In recommendation systems, popularity plays a key role in determining content relevance, as more popular Points-of-Interest tend to better meet the needs of a broader user base. The absence of this factor in the VIKOR-WP method has led to a decrease in accuracy compared to some other methods, especially at moderate values of N, such as N=10, where this issue becomes more noticeable.

The VIKOR-WS method, shown in the red chart, does not consider users' social relationship information. Social relationships have a significant impact on personalized recommendations, as users are often interested in items or topics that have gained attention in their social networks. The lack of this information has led to lower accuracy for this method, especially at higher values of N, compared to some more advanced methods. The VIKOR-WPW method, shown in the green chart, uses the VIKOR neutrosophic framework but assigns equal weights to all features. While this approach provides relatively acceptable performance due to its comprehensiveness and consideration of all features (topic interests, popularity, social relationships), ignoring the weight differences between features can limit its efficiency. For example, in many situations, a specific feature (such as popularity) may be more important, and assigning equal weight to all features may result in suboptimal outcomes. The superior performance of VIKOR-NS, seen in the blue chart, is because it uses the relevant information more comprehensively and accurately, demonstrating better performance at all values of N, particularly at N=15. This advantage may stem from using a framework that considers all features proportionally with appropriate weights, or it may result from more advanced data analysis modeling.

Methods that ignore key information such as personal preferences, popularity, and social relationships tend to perform poorly. The VIKOR-NS method, due to its more comprehensive consideration of features and the adjustment of weights proportionally in an objective manner using the CRITIC method, achieves higher accuracy. This indicates that personalization and the use of frameworks that consider features according to their respective importance are crucial for improving the performance of recommendation systems.

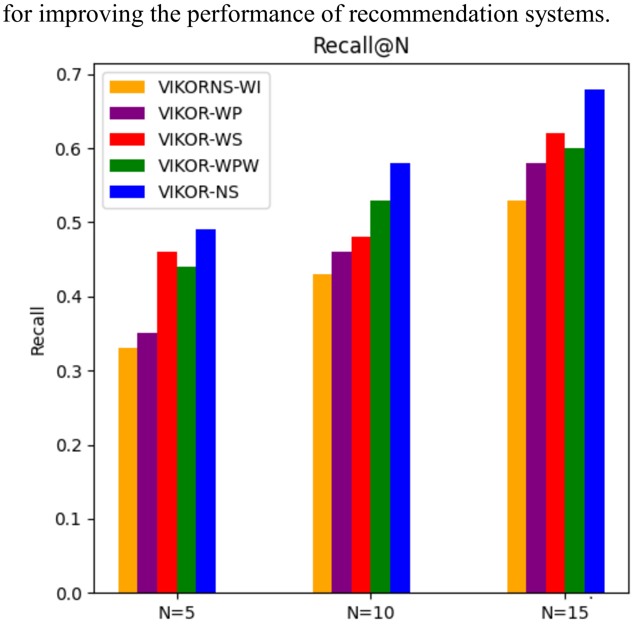

Fig 3. The chart related to Recall based on the number of listed Points-of-Interest

Figure 3 shows the Recall chart for five different algorithms in three scenarios: N=5, N=10, and N=15. Recall is the number of relevant locations that users have examined among the top N suggested locations, relative to the total number of relevant locations that users have examined in the test set. In other words, it measures the proportion of relevant items that were found by the algorithm. VIKOR-NS, represented by the blue chart, performed the best in terms of Recall in all three scenarios, especially at N=15. This indicates that this algorithm was able to find a higher proportion of correct items compared to the other algorithms. As shown in the green chart, VIKOR-WPW performed relatively well and, in all three scenarios, its value was above 0.5. This algorithm also performed acceptably in terms of finding correct items. The algorithms that did not consider the relevant criteria performed worse than the two previous algorithms and had lower Recall values. This indicates that these algorithms were weaker in finding correct items compared to the other two algorithms. A high Recall means a greater coverage of correct items. The higher this value, the more items the algorithm was able to find. However, the most important parameter that indicates the quality of ranking is NDCG, and the chart of its values can be seen in Figure 4.

Figure 3 shows the Recall chart for five different algorithms in three scenarios: N=5, N=10, and N=15. Recall is the number of relevant locations that users have examined among the top N suggested locations, relative to the total number of relevant locations that users have examined in the test set. In other words, it measures the proportion of relevant items that were found by the algorithm. VIKOR-NS, represented by the blue chart, performed the best in terms of Recall in all three scenarios, especially at N=15. This indicates that this algorithm was able to find a higher proportion of correct items compared to the other algorithms. As shown in the green chart, VIKOR-WPW performed relatively well and, in all three scenarios, its value was above 0.5. This algorithm also performed acceptably in terms of finding correct items. The algorithms that did not consider the relevant criteria performed worse than the two previous algorithms and had lower Recall values. This indicates that these algorithms were weaker in finding correct items compared to the other two algorithms. A high Recall means a greater coverage of correct items. The higher this value, the more items the algorithm was able to find. However, the most important parameter that indicates the quality of ranking is NDCG, and the chart of its values can be seen in Figure 4.

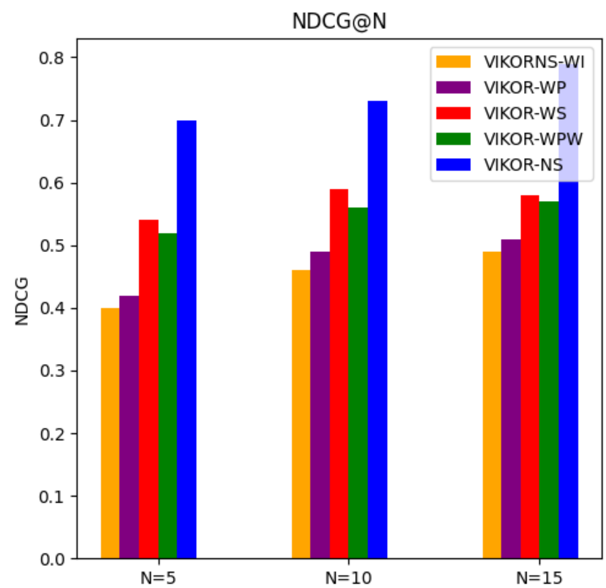

Fig4. Chart of NDCG based on the number of listed Points-of-Interest

Figure 4 shows the NDCG@N chart for five different algorithms: VIKORNS-WI, VIKOR-WP, VIKOR-WS, VIKOR-WPW, and VIKORNS, in three scenarios: N=5, N=10, and N=15. This metric is an evaluation criterion used to measure the quality of the ranking results. It indicates how much the ranked results match the ideal order. In other words, NDCG shows whether more important results are ranked higher. The horizontal axis shows for how many top results the NDCG metric has been calculated. For example, NDCG@5 refers to the metric calculated for the top 5 results, and NDCG@10 for the top 10 results. The larger the value of N, the more results are considered for calculation. The NDCG axis ranges from 0 to 1. The closer the NDCG value is to 1, the better the ranking.

Based on the chart, it can be observed that VIKORNS, represented by the blue chart, performs the best in all three scenarios of N and achieves the highest NDCG. This indicates that this algorithm provides the best ranking and places more important results at higher ranks, which is due to incorporating all parameters and appropriately weighting the criteria. The orange chart, which has the lowest value, indicates that without considering attractiveness, prioritization lacks quality.

4-3. Comparison of the Proposed Algorithm with the MMPOI Algorithm

The performance of the proposed method on the Yelp and Foursquare datasets is summarized in Table 3. In this table, the performance of MMPOI is presented as the baseline method for comparison. In both the baseline method and the proposed method, the Yelp and Foursquare datasets are pre-filtered, meaning that less popular locations and users with fewer than 10 recorded check-ins are removed. Then, multimedia information such as images and reviews related to locations is collected for the MMPOI method to ensure that each location in the dataset contains three types of information: images, user reviews, and metadata (descriptions and/or categories).

In the proposed method, user relationship graphs replace image analysis. Additionally, topic relevance and popularity are utilized, and only sentiment analysis is performed, whereas in MMPOI, the main framework relies on text analysis. Furthermore, in both compared methods, the sequence of user check-ins is segmented based on 24-hour intervals. Specifically, sequences that contain only one check-in after segmentation are removed. Finally, the datasets are split into 80% for training and 20% for testing. The dataset details are provided in Table 3.

Table 3. Comparison of the Performance of the Proposed Method with MMPOI on the Yelp and Foursquare Datasets

	New_orleans			Philadelphia		
method	HR@5	HR@20	NDCG@20	HR@5	HR@20	NDCG@20
MMPOI	0.3123	0.1151	0.3521	0.1987	0.7398	0.02564
Proposal method	0.3422	0.1317	0.3829	0.2345	0.8977	0.3876

In this table, the average values from the Yelp and Foursquare datasets have been taken. Firstly, the proposed model significantly outperforms the state-of-the-art location recommendation methods, such as MMPOI, on both datasets. We attribute this performance improvement to the effective integration of multimedia information of locations with users' check-in sequences and the use of user connection graphs instead of images. Additionally, the criteria used in our approach, namely popularity and topic, provide better results. We incorporate sentiment analysis into our framework in a small yet effective manner, and simulations demonstrate that it is more efficient than the MMPOI method.

5. Conclusion

Location-based recommendation systems play a crucial role in enhancing user experiences across various domains. In this study, the proposed model was designed to improve recommendation accuracy by analyzing existing challenges. This model incorporates spatial data processing, optimizing the recommendation system with machine learning algorithms in different framework sections, and utilizing a neutrosophic multi-criteria decision-making model. The results demonstrated that the proposed framework increased recommendation accuracy by up to 15% and improved user acceptance of suggestions.

To evaluate the model, datasets from various platforms were used, and the results indicated that the proposed method outperformed traditional algorithms. Various metrics such as precision, recall rate, and NDCG were employed to analyze the model’s efficiency, revealing that the combination of clustering methods and multi-criteria decision-making significantly optimized the recommendation process. Additionally, the use of neutrosophic logic in processing uncertain data played a crucial role in reducing information noise and increasing system accuracy.

The choice of algorithms within this proposed framework—such as the Imperialist Competitive Algorithm (ICA) for initial clustering, Fuzzy C-Means for flexible membership, neutrosophic VIKOR for ranking requirements, and CRITIC for weight assessment—was grounded in their respective strengths. ICA efficiently identifies clusters in complex spatial data, while Fuzzy C-Means allows for nuanced user preferences through soft clustering. Neutrosophic VIKOR expertly handles uncertainties in multi-criteria decision-making, and CRITIC provides an objective approach to assessing criteria importance. Each of these choices contributes to enhancing the accuracy and robustness of the recommendations provided by the system.

Exploring the integration of multi-criteria decision-making methods with graph models and social network analysis can also open new avenues for improving recommendation quality. Given that social interactions and relationships between users significantly influence their decision-making, employing network analysis algorithms to identify user groups and generate recommendations based on social connections can enhance the performance of recommendation systems.

Overall, expanding research in these areas could lead to the development of a new generation of location-based recommendation systems that, in addition to higher accuracy and quality, offer greater adaptability to environmental conditions and user needs. Another potential research direction for the future is improving interactions and integration between recommendation systems and other intelligent systems. For example, location-based recommendation systems could be integrated with urban traffic management or intelligent transportation systems to provide suggestions that not only align with individual preferences but also contribute to optimizing urban resource utilization. This integration could enable recommendation systems to offer more up-to-date suggestions that best meet user needs.

Furthermore, considering cultural and geographical diversity in the design of recommendation systems could provide a new research path. Cultural differences and user preferences in different locations can significantly impact the type of recommendations and choices. Future studies could specifically focus on how recommendation systems can be adapted to the needs of users in various geographic regions while taking cultural and social differences into account.

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Appendix A

1. **Cr**iteria **I**mportance **T**hrough **I**nter-criteria **C**orrelation(CRITIC)
2. Normalized Discounted Cumulative Gain(NDCG)
3. VIKOR Neutrosphic without Interest topic(VNWI)
4. VIKOR Neutrosphic without Popularity(VNWP)
5. VIKOR Neutrosphic without Social network(VNWS)
6. VIKOR Neutrosphic without Personalized Weighting(VNWPW)