Interdisciplinary Journal of Information, Knowledge, and Management

An Official Publication of the Informing Science Institute InformingScience.org

IJIKM.org

Volume 19, 2024

PERSONALIZED TOURISM RECOMMENDATIONS: LEVERAGING USER PREFERENCES AND TRUST NETWORK

Qusai Yousef Shambour*	Department of Software Engineering, Faculty of Information Technology, Al-Ahliyya Amman University, Amman, Jordan	q.shambour@ammanu.edu.jo
Mosleh M. Abualhaj	Department of Networks and Cybersecurity, Faculty of Information Technology, Al-Ahliyya Amman University, Amman, Jordan	m.abualhaj@ammanu.edu.jo
Ahmad Adel Abu-Shareha	Department of Data Science and Artificial Intelligence, Faculty of Information Technology, Al-Ahliyya Amman University, Amman, Jordan	a.abushareha@ammanu.edu.jo
Qasem M. Kharma	Department of Software Engineering, Faculty of Information Technology, Al-Ahliyya Amman University, Amman, Jordan	q.kharma@ammanu.edu.jo

* Corresponding author

ABSTRACT

Aim/Purpose	This study aims to develop a solution for personalized tourism recommendations that addresses information overload, data sparsity, and the cold-start problem. It focuses on enabling tourists to choose the most suitable tourism-related facilities, such as restaurants and hotels, that match their individual needs and preferences.
Background	The tourism industry is experiencing a significant shift towards digitalization due to the increasing use of online platforms and the abundance of user data. Travelers now heavily rely on online resources to explore destinations and associated options like hotels, restaurants, attractions, transportation, and events. In

Accepting Editor Tharrenos Bratitsis │ Received: March 12, 2024 │ Revised: May 22, June 16, 2024 │ Accepted: June 17, 2024.

Cite as: Shambour, Q. Y., Abualhaj, M. M., Abu-Shareha, A. A., & Kharma, Q. M. (2024). Personalized tourism recommendations: Leveraging user preferences and trust network. *Interdisciplinary Journal of Information, Knowledge, and Management, 19,* Article 17. https://doi.org/10.28945/5329

this dynamic landscape, personalized recommendation systems play a crucial role in enhancing user experience and ensuring customer satisfaction. However, existing recommendation systems encounter major challenges in precisely understanding the complexities of user preferences within the tourism domain. Traditional approaches often rely solely on user ratings, neglecting the complex nature of travel choices. Data sparsity further complicates the issue, as users might have limited interactions with the system or incomplete preference profiles. This sparsity can hinder the effectiveness of these systems, leading to inaccurate or irrelevant recommendations. The cold-start problem presents another challenge, particularly with new users who lack a substantial interaction history within the system, thereby complicating the task of recommending relevant options. These limitations can greatly hinder the performance of recommendation systems and ultimately reduce user satisfaction with the overall experience.

Methodology

The proposed User-based Multi-Criteria Trust-aware Collaborative Filtering (UMCTCF) approach exploits two key aspects to enhance both the accuracy and coverage of recommendations within tourism recommender systems: multi-criteria user preferences and implicit trust networks. Multi-criteria ratings capture the various factors that influence user preferences for specific tourism items, such as restaurants or hotels. These factors surpass a simple one-star rating and take into account the complex nature of travel choices. Implicit trust relationships refer to connections between users that are established through shared interests and past interactions without the need for explicit trust declarations. By integrating these elements, UMCTCF aims to provide more accurate and reliable recommendations, especially when data sparsity limits the ability to accurately predict user preferences, particularly for new users. Furthermore, the approach employs a switch hybridization scheme, which combines predictions from different components within UMCTCF. This scheme leads to a more robust recommendation strategy by leveraging diverse sources of information. Extensive experiments were conducted using real-world tourism datasets encompassing restaurants and hotels to evaluate the effectiveness of UMCTCF. The performance of UMCTCF was then compared against baseline methods to assess its prediction accuracy and coverage.

Contribution

This study introduces a novel and effective recommendation approach, UMCTCF, which addresses the limitations of existing methods in personalized tourism recommendations by offering several key contributions. First, it transcends simple item preferences by incorporating multi-criteria user preferences. This allows UMCTCF to consider the various factors that users prioritize when making tourism decisions, leading to a more comprehensive understanding of user choices and, ultimately, more accurate recommendations. Second, UMCTCF leverages the collective wisdom of users by incorporating an implicit trust network into the recommendation process. By incorporating these trust relationships into the recommendation process, UMCTCF enhances its effectiveness, particularly in scenarios with data sparsity or new users with limited interaction history. Finally, UMCTCF demonstrates robustness towards data sparsity and the cold-start problem. This resilience in situations with limited data or incomplete user profiles makes UMCTCF particularly suitable for real-world applications in the tourism domain.

Findings

The results consistently demonstrated UMCTCF's superiority in key metrics, effectively addressing the challenges of data sparsity and new users while enhancing both prediction accuracy and coverage. In terms of prediction accuracy, UMCTCF yielded significantly more accurate predictions of user preferences for tourism items compared to baseline methods. Furthermore, UMCTCF achieved superior coverage compared to baseline methods, signifying its ability to recommend a wider range of tourism items, particularly for new users who might have limited interaction history within the system. This increased coverage has the potential to enhance user satisfaction by offering a more diverse and enriching set of recommendations. These findings collectively highlight the effectiveness of UMCTCF in addressing the challenges of personalized tourism recommendations, paving the way for improved user satisfaction and decision-making within the tourism domain.

Recommendations for Practitioners The proposed UMCTCF approach offers a potential opportunity for tourism recommendation systems, enabling practitioners to create solutions that prioritize the needs and preferences of users. By incorporating UMCTCF into online tourism platforms, tourists can utilize its capabilities to make well-informed decisions when selecting tourism-related facilities. Furthermore, UMCTCF's robust design allows it to function effectively even in scenarios with data sparsity or new users with limited interaction history. This characteristic makes UMCTCF particularly valuable for real-world applications, especially in scenarios where these limitations are common obstacles.

Recommendations for Researchers The success of UMCTCF can open up new avenues in personalized recommendation research. One promising direction lies in exploring the integration of additional contextual information, such as temporal (time-based) or location-based information. By incorporating these elements, the model could be further improved, allowing for even more personalized recommendations. Furthermore, exploring the potential of UMCTCF in domains other than tourism has considerable significance. By exploring its effectiveness in other e-commerce domains, researchers can broaden the impact of UMCTCF and contribute to the advancement of personalized recommendation systems across various industries.

Impact on Society UMCTCF has the potential to make a positive impact on society in various ways. By delivering accurate and diverse recommendations that are tailored to individual user preferences, UMCTCF fosters a more positive and rewarding user experience with tourism recommendation systems. This can lead to increased user engagement with tourism platforms, ultimately enhancing overall satisfaction with travel planning. Furthermore, UMCTCF enables users to make more informed decisions through broader and more accurate recommendations, potentially reducing planning stress and leading to more fulfilling travel experiences.

Future Research Expanding upon the success of UMCTCF, future research activities can explore several promising paths. Enriching UMCTCF with various contextual data, such as spatial or location-based data, to enhance recommendation accuracy and relevance. Leveraging user-generated content, like reviews and social media posts, could provide deeper insights into user preferences and sentiments, improving personalization. Additionally, applying UMCTCF in various e-commerce domains beyond tourism, such as online shopping, entertainment, and healthcare, could yield valuable insights and enhance recommendation systems. Finally, exploring the integration of optimization algorithms could improve both recommendation accuracy and efficiency.

Keywords tourism recommendation, multi-criteria analysis, implicit trust network, data sparsity, cold start, new user

INTRODUCTION

The exponential growth of both online information and internet users over the past decade has led to the overwhelming quantity of data presented in response to search queries. This information overload often requires significant time and effort from users to navigate through the overwhelming amount of information and select options that meet their particular requirements. The tourism industry exemplifies the challenges of information overload. Travelers planning a trip must navigate decisions not only about destinations but also a wide range of associated tourism-related facilities such as hotels, restaurants, attractions, transportation, and events. Recommender systems offer a promising solution to address the challenges of information overload. These systems analyze explicit or implicit user feedback to identify individual preferences and subsequently match these preferences with corresponding characteristics of tourism offerings. These personalized systems facilitate a more manageable selection process, aiding travelers in decision-making (Hong & Jung, 2021; Ricci, 2022).

Collaborative Filtering (CF) represents a fundamental and widely adopted methodology to recommend items across various domains. However, traditional CF-based recommendation systems face limitations. First, CF-based recommender systems often rely on a single rating score, which may not fully reflect the multifaceted nature of user preferences. In the context of the tourism domain, such as hotel or restaurant recommendations, multi-criteria ratings (e.g., facilities, location, staff, food, service) offer richer insights into user preferences. Platforms like Tripadvisor.com demonstrate the practical collection of this valuable data. Second, CF-based recommender systems often face issues with data sparsity and cold start. Data sparsity occurs when the amount of user-item interaction data available for a user is much less than the amount needed to accurately predict user preferences. The cold-start problem arises when a system does not have sufficient historical data for new users, which hinders the ability to generate personalized recommendations. The limitations interfere with the accurate modeling of preferences and the delivery of personalized recommendations (Adomavicius & Kwon, 2007; Aggarwal, 2016b; Ko et al., 2022).

Consider a real-world scenario where a tourism recommender system aims to provide personalized recommendations for local attractions, restaurants, and accommodations based on user preferences. In such a scenario, data sparsity can pose a significant challenge when the system attempts to recommend attractions to a tourist with limited interaction history. Without sufficient user-item interaction data, the system may find it challenging to accurately predict the tourist's preferences, leading to less personalized recommendations. This issue is further compounded by the cold-start problem, which significantly restricts the system's ability to generate personalized recommendations for new tourists. Since the system lacks historical data for these tourists, it cannot rely on past interactions to tailor recommendations to their preferences. As a result, new tourists may receive generic or irrelevant recommendations, potentially leading to a poor travel experience and diminished user satisfaction.

To address the limitation of relying solely on a single rating score, which does not fully represent the complex nature of user decision-making, research has explored the development of Multi-Criteria (MC) recommender systems. Such systems leverage additional rating data that reveals users' preferences for specific features of items. By incorporating this richer data, MC-based CF can improve recommendation accuracy. These systems consider the critical aspects that impact users' item selection during the recommendation process, resulting in more accurate and effective recommendations (Shambour et al., 2021, 2022, 2023). Furthermore, to address the limitations imposed by data sparsity and the cold-start problem in CF-based systems, recent research has investigated the integration of supplementary information alongside user ratings. Social trust networks emerge as a promising solution in this context. These networks function as additional data sources, revealing user preferences for items through their interactions within the network. Moreover, they uncover trust relationships among users, offering insights into possible user influence. Utilizing this rich social information allows recommender systems to produce more accurate, diverse, and personalized recommendations, effectively addressing data sparsity and cold-start problems (Camacho & Alves-Souza, 2018;

Shambour & Lu, 2011). However, a key challenge associated with social trust networks is the sparsity of explicit relationships within the network itself. To overcome this limitation, research has explored incorporating implicit relationships into the recommendation process. This approach focuses on identifying potential connections between users based on their interactions with items, even if they haven't explicitly declared a trust relationship (Ahmadian et al., 2020).

Drawing on the limitations highlighted earlier and inspired by the success achieved through the fusion of various methodologies in recommender systems (Burke, 2007; Ko et al., 2022; Shambour et al., 2020), this study introduces a novel User-based Multi-Criteria Trust-aware Collaborative Filtering (UMCTCF) approach for personalized tourism recommendations. The primary objective of this approach is to enhance the accuracy, diversity, and personalization of tourism recommendations for tourists by assisting them in making well-informed choices when selecting from various tourism-related facilities such as restaurants, hotels, and museums that suit their individual needs and preferences. The proposed UMCTCF approach addresses the challenge of personalized tourism recommendations by integrating multi-criteria user preferences and implicit trust networks. This integration aims to enhance both the accuracy and coverage of recommendations within the system. UMCTCF comprises three key components:

- User-based Multi-Criteria Collaborative Filtering: This component analyzes user preferences beyond simple ratings, considering multiple criteria to gain a richer understanding of individual needs, thereby generating more precise personalized tourism recommendations.
- User-based Multi-Criteria Trust Filtering: This component enhances recommendation quality by incorporating implicit trust relationships between users. By identifying users with similar interests, UMCTCF can leverage their recommendations, even if they are not directly connected. This is particularly beneficial for situations where data sparsity or new users limit the effectiveness of traditional CF-based recommendation methods.
- Fusion Recommendation: This final component intelligently combines the outputs from the previous two components using a switch hybridization scheme. This approach exploits the strengths of both components to provide comprehensive and personalized tourism recommendations.

Together, these components improve recommendation quality by considering diverse user preferences and tapping into collective user wisdom beyond direct connections. This ultimately leads to a more enriching travel experience, notably in scenarios with sparse data or new users, where traditional recommendation methods struggle to make accurate recommendations.

A thorough experimental evaluation was carried out to assess the proposed approach, using two real-world tourism datasets: Restaurants-TripAdvisor and Hotels-TripAdvisor, along with other datasets featuring different levels of data sparsity and new user scenarios. Based on the experimental results, UMCTCF consistently outperforms the baseline methods across different metrics. It attains a notably higher prediction accuracy, indicating that its recommendations better match user preferences. Additionally, UMCTCF demonstrates excellent coverage, indicating its capability to recommend a wide range of options with specific tourism facilities. It is especially advantageous for individuals looking for a variety of travel experiences or discovering less popular destinations. In addition, the UMCTCF shows resilience to data sparsity and the cold-start problem, making it ideal for practical applications with limited data availability. The rest of this paper adheres to a well-organized layout. It commences with a concise overview of the current literature on recommender systems in tourism. Following this, the design methodology of the UMCTCF approach is outlined. The final sections will present the evaluation experiments, concluding with recommendations for further research.

RELATED WORK

RECOMMENDER SYSTEMS IN TOURISM

Recommender systems have experienced a substantial increase in popularity in the past decade, demonstrating their effectiveness in various domains (Ko et al., 2022). Within the tourism industry, recommender systems are now widely used in various tourism applications (Chaudhari & Thakkar, 2020; Ricci, 2022; Sarkar et al., 2023). These systems offer tourists valuable tools for trip planning, encompassing a wide range of recommendations, including hotels, restaurants, transportation options, travel packages, museums, and various other travel-related services.

A core focus of research in tourism recommender systems lies in developing techniques to personalize recommendations for a wide range of user preferences. Kulkarni et al. (2019) propose a machine-learning approach that leverages sentiment analysis of user reviews. By analyzing the sentiment behind user ratings, the system can understand user interests beyond basic numerical scores and recommend tourist attractions that align with these interests. Esmaeili et al. (2020) introduce a novel tourism recommender system that incorporates social commerce aspects into the recommendation process. Their system considers factors such as trust, reputation, and social relationships within a user's network to provide personalized recommendations based on the user's social context. Maru'ao and Suharjito (2021) present a tourism recommender system using a hybrid multi-criteria approach. The system aims to provide destination recommendations to users based on their preferences by combining various methods, including content-based, collaborative filtering, multi-criteria ratings, demographic, and ontology-based approaches. Addressing the challenge of data sparsity and cold-start problems, which often plague recommender systems, Nan et al. (2022) introduce the Collaborative Mining and Filtering Process (CMFP) approach. This approach leverages knowledge-based transfer learning to improve the efficiency and accuracy of personalized recommendations, especially for new users or tourist destinations with limited data. By analyzing accumulated data from various sources, including global and personal travel information, the CMFP provides a more robust foundation for generating accurate recommendations, even in scenarios with limited data availability. Chalkiadakis et al. (2023) present a novel hybrid recommender system for the tourism domain that combines a Bayesian preference elicitation component with a content-based recommendation component. This hybrid approach aims to address the challenge of accurately capturing user preferences, which can be subjective and multifaceted. The system utilizes semantic similarity measures to identify points of interest that are content-wise relevant to the user's preferences, further enhancing the personalization of recommendations.

The hospitality industry traditionally relied on travel agents and in-person booking for hotel selection. However, the rise of online booking platforms has shifted consumer preference towards online options. While convenient, manually searching and comparing hotels online can be time-consuming, highlighting the need for personalized hotel recommendation systems to assist travelers in making informed choices. Recognizing this need, Hassan and Abdulwahhab (2019) propose a location-based sentiment analyzer for hotel recommender systems. This approach goes beyond traditional rating-based systems by considering user location and sentiment expressed in reviews to offer more detailed insights into hotel quality and services. By analyzing user reviews and identifying positive and negative aspects of hotels, the system can provide tourists with a more comprehensive picture of potential accommodation options, enabling them to make informed decisions based on their specific needs and preferences. Yadav et al. (2020) present a user-centric approach that recommends hotels in a given geographical area based on user queries. This system allows tourists to actively participate in the recommendation process by specifying their desired location, price range, and other criteria. The system then retrieves relevant hotels from the database and presents them to the user, allowing them to compare options and make informed choices. Ray et al. (2021) introduce an ensemble-based hotel recommender system that utilizes sentiment analysis and aspect-based opinion mining of hotel reviews. It utilizes a combination of advanced techniques, including the Bidirectional Encoder Representations from Transformers (BERT) model, a Random Forest classifier, fuzzy logic, and cosine similarity, to extract detailed insights from user reviews. This fine-grained analysis allows the system to provide more personalized recommendations for hotels that serve the unique needs and preferences of individual tourists. Cui et al. (2022) address the challenge of ambiguity and uncertainty in user reviews by proposing a hotel recommendation approach that utilizes probabilistic linguistic term sets (PLTS). The proposed approach translates user statements into PLTSs, which capture the inherent subjectivity and vagueness of natural language. By considering the probabilistic nature of linguistic terms, the system can provide more accurate recommendations that reflect the user's true sentiment towards different hotels. The effectiveness and superiority of the proposed approach are demonstrated through a case application and comparative analysis with other recommendation methods using hotels in Zhengzhou. Ganji et al. (2023) propose a method that utilizes sentiment analysis, deep learning, and data balancing techniques to improve the quality of decision-making in hotel recommender systems. Their method addresses the issue of biased or imbalanced datasets by employing data-balancing techniques. Additionally, they leverage transformer-based models with attention mechanisms for sentiment analysis, achieving higher accuracy in sentiment classification compared to previous methods.

While recommender systems are widely used in a variety of tourism applications, their use extends beyond hospitality to the culinary industry, where they play an important role in simplifying the dining experience. The culinary industry is experiencing a boom, with new restaurants offering diverse menus to attract customers. However, choosing a restaurant can be overwhelming due to the sheer number of options. Fortunately, restaurant recommender systems address this challenge by leveraging user data and intelligent algorithms to generate personalized recommendations, simplifying the dining experience. Sun et al. (2019) exemplify this by introducing a novel approach to restaurant recommendations that leverages sentiment analysis of online Chinese reviews while incorporating uncertainty theory. This approach accounts for the uncertainty associated with user sentiment by utilizing uncertain sets and variables. Additionally, they introduce a distance-based approach to identify similar reviewers' opinions, enhancing the system's ability to identify user preferences and recommend restaurants that align with these preferences. Hartanto and Utama (2020) present a decision support model for restaurant recommendations that consider multi-parameters like customer interest, budget, distance, taste and cleanliness ratings, and even halal or non-halal status for a more comprehensive understanding of user preferences. The model uses fuzzy logic, cosine similarity distance, selection, and optimization methods to provide personalized restaurant recommendations tailored to individual or group needs. Asani et al. (2021) propose a personalized restaurant recommender system that leverages sentiment analysis and context awareness. Their system analyzes user comments to identify food names and the associated sentiment, allowing them to understand user preferences for specific cuisines. This enables the system to recommend nearby open restaurants that are tailored to the user's specific food preferences, leading to a more satisfying dining experience. Savchenko (2022) introduces a novel approach that utilizes user-generated photos to address the cold-start problem, which often occurs when recommending new restaurants with limited data. Their system leverages scene recognition and multi-task convolutional neural networks to analyze photos of restaurants from the user's mobile device gallery. By identifying the type of cuisine depicted in the photos, the system can create a profile of the user's gastronomic preferences. This profile, combined with additional attributes like restaurant ratings, allows the system to recommend restaurants in a new city that align with the user's preferences, even if the restaurant has limited data available. Perumal et al. (2023) propose an ontology-based recommendation system for restaurants. Ontologies define hierarchical relationships between concepts, which, in this case, can represent different types of cuisines, restaurant amenities, and user preferences. This approach allows the system to address the cold-start problem by utilizing the defined relationships within the ontology to recommend restaurants even when limited data is available. For a comprehensive overview of related work, refer to Table 1. This table presents a comparison of methods used and key features, advantages, and limitations of selected studies within the field.

Table 1. Summary of related work

Study	Method	Key features	Advantages	Limitations
Kulkarni et al. (2019)	Sentiment analysis	Analyzes user reviews for sentiment to understand interests beyond numerical scores	Captures nuanced user preferences; improves accuracy	Data sparsity and contextual ambiguity in user reviews; requires extensive data for training; requires substantial computational resources
Esmaeili et al. (2020)	Social analysis, collaborative filtering, content-based filtering	Incorporates trust, reputation, and social relationships into recommendations	Leverages social context for personalized recommendations	Complex implementation; relies heavily on explicit social data availability
Maru'ao and Suharjito (2021)	Content-based, collaborative filtering, multi-criteria ratings, demographic, and ontology-based	Combines multiple recommendation methods	Addresses diverse user preferences; improves accuracy	Complex system integration; potential high computational cost
Nan et al. (2022)	Collaborative mining and filtering, knowledge-based transfer learning	Uses collaborative mining and filtering process for context-aware travel recommendations	Reduces the data processing overheads; improves accuracy	Requires extensive data sources
Chalkiadakis et al. (2023)	Bayesian preference elicitation, content-based filtering	Utilizes semantic similarity for personalized recommendations	Reduces the impact of the cold-start problem; accurately captures multifaceted user preferences	Requires substantial computational resources
Hassan and Abdulwahhab (2019)	Location-sentiment based recommendation method	Considers user location and review sentiment for hotel recommendations	Provides detailed insights into hotel quality and services	Data sparsity and contextual ambiguity in user reviews; dependent on the availability of location data
Ray et al. (2021)	Sentiment analysis	Uses BERT, Random-forest, and fuzzy logic for detailed review analysis	Fine-grained, personalized hotel recommendations	Data sparsity and contextual ambiguity in user reviews; high complexity; potentially resource-intensive
Cui et al. (2022)	Sentiment analysis	Translates user reviews into linguistic term sets to handle ambiguity	Captures subjectivity and vagueness in natural language	Data sparsity and contextual ambiguity in user reviews; handling probabilistic terms can be complex
Ganji et al. (2023)	Sentiment analysis	Uses deep learning and data balancing for improved sentiment classification	Higher accuracy in sentiment analysis	Data sparsity and contextual ambiguity in user reviews; requires substantial data processing
Sun et al. (2019)	Sentiment analysis	leverages uncertain sets and uncertainty statistics to estimate unknown user opinion values in reviews	Improved identification of user preferences	Data sparsity and contextual ambiguity in user reviews; requires substantial data processing; data privacy concerns

Study	Method	Key features	Advantages	Limitations
Hartanto and Utama (2020)	Fuzzy logic, cosine similarity distance, selection, and optimization	Considers diverse parameters for comprehensive restaurant recommendations	Tailored to individual and group needs	Complex model; requires detailed user input
Asani et al. (2021)	Sentiment analysis, context-awareness	Analyzes comments for specific food preferences	Enhanced dining experience through context-aware recommendations	Data sparsity and contextual ambiguity in user reviews; context data can be difficult to capture
Savchenko (2022)	Scene recognition	Uses user-generated photos to address cold-start problem	Effective recommendations with limited data	Dependent on the quality and relevance of user photos
Perumal et al. (2023)	Ontology-based	Utilizes hierarchical relationships for restaurant recommendations	Effective recommendations with limited data	Complexity in creating and maintaining ontologies

DESIGN METHODOLOGY

This study introduces a novel UMCTCF approach applicable to tourism recommendation systems, consisting of three main components, as depicted in Figure 1. The first component is the User-based Multi-Criteria Collaborative Filtering, which uses a user-based collaborative filtering technique to generate recommendations based on similar users' preferences and historical multi-criteria ratings. It incorporates multi-criteria analysis to consider various aspects of users' preferences. The second component is the User-based Multi-Criteria Trust Filtering, which enhances recommendations by utilizing implicit trust relationships between users. Lastly, the Fusion Recommendation component intelligently combines the outputs from the previous two components, exploiting their strengths to provide comprehensive and personalized tourism-related recommendations.

PRELIMINARIES

To clarify the proposed recommendation approach, we introduce the following fundamental concepts:
Users: Denoted by $U = \{u_1, u_2, \dots u_m\}$, this represents a set of m users within an online community who have interacted with and rated various items.
Items: Represented by $I = \{i_1, i_2, \dots i_n\}$, this set encompasses the m items rated by users in U.
Multi-Criteria Ratings: Our user-item rating matrix, R_{m*n*k}, captures diverse criteria for each item. Specifically, let $C = \{c_1, c_2, \dots, c_k\}$ be a list of criteria used to assess item i. Each criterion represents a distinct aspect of the item, receiving a rating value from users. The total utility U for user a of item i is represented as an additive value function following the Multi-Attribute Utility Theory (Dyer, 2005):

$$U^a(i) = \sum_{c=1}^{k} w_c^a(i) \times r_c^a(i) \ , \ \ where \sum_{c=1}^{k} w_c^a(i) = 1 \tag{1}$$

where $w_c^a(i)$ denotes the weight assigned by user a to criterion c for item i, reflecting its significance. $r_c^a(i)$ represents the rating provided by user a on criterion c for item i. This equation sums the weighted ratings across all criteria to compute the overall utility (overall rating) of an item for a user.
Implicit Trust Network: is modeled as a directed graph G = (U, E, ω), where U is the set of nodes, representing users, E is a set of edges, signifying implicit trust relationships between users, and ω is the edge weight signifying the implicit trust score between each user pair.

THE RECOMMENDATION PROCESS

In this section, we will outline the recommendation process of the UMCTCF approach, which combines user-based MC CF and user-based MC trust filtering techniques. The recommendation process consists of three main components. Figure 1 showcases the components included in the proposed UMCTCF approach.

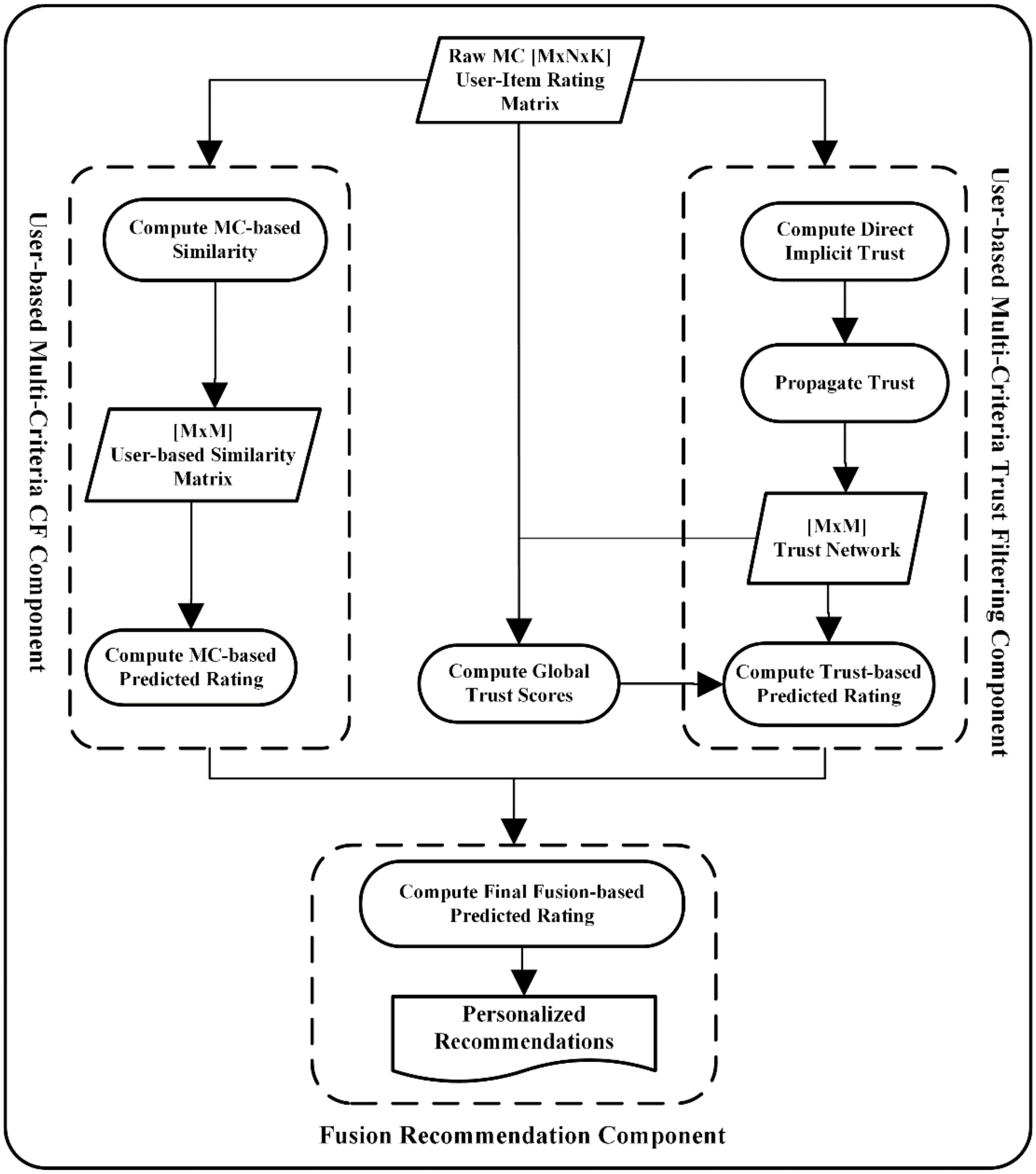

Figure 1. The framework of the proposed UMCTCF approach

The User-based Multi-Criteria Collaborative Filtering Component

Step 1: Compute the similarity between users based on their ratings on co-rated items

In this step, the Absolute Difference of Ratings (ADF) method (Gazdar & Hidri, 2020) is initially utilized to quantify partial similarities between the active user *a* and each user *b*. The method calculates these similarities for each rating criterion *c* based on the items they have both rated, as shown below.

$$ADF^{c}_{a,b} = \frac{\sum_{i=1}^{I_{a \cap b}} \exp\left(- \frac{\left| r^{c}_{a,i} - r^{c}_{b,i} \right|}{max\left(r^{c}_{a,i},\ r^{c}_{b,i} \right)} \right)}{I_{a \cap b}} \tag{2}$$

Where $r^{c}_{a,i}$ and $r^{c}_{b,i}$ represent the ratings of users *a* and *b* on item *i* concerning criterion *c*, $I_{a \cap b}$ denotes the total number of items commonly rated among users *a* and *b*. This equation computes the average absolute difference in ratings between two users for a specific criterion, providing a measure of their similarity.

Then, the total ADF similarity score among users *a* and *b* is derived by aggregating all partial similarities (calculated for each available criterion) using the worst-case similarity approach (Adomavicius & Kwon, 2007), as follows.

$$Sim^{ADF}_{a,b} = \min_{c=1,\ldots,k} ADF^{c}_{a,b} \tag{3}$$

Where *k* denotes the number of available rating criteria. This aggregation method ensures that the overall similarity score reflects the lowest similarity across all criteria.

Step 2: Compute the similarity between users based on all recorded ratings

However, the ADF method depends only on co-rated items, making it ineffective in sparse datasets where such items are limited or absent. To overcome this limitation, we utilize the Bhattacharyya Coefficient (Patra et al., 2015) as an alternative method to measure similarity when there are few or no co-rated items. This measure utilizes the entire collection of recorded ratings from both users to calculate their similarity via the following formula:

$$Sim^{BH}_{a,b} = \sum_{i \in I} \sum_{j \in J} BC(i, j) \times loc(r_{a,i}, r_{b,j}) \tag{4}$$

Both *BC* and *loc* serve as similarity metrics among users, but they rely on different information sources. *BC* uses global information, while *loc* relies on local information. *I* and *J* are the sets of items rated by users *a* and *b*, respectively. Consequently, *BC* is initially utilized to compute the partial similarities between items *i* and *j* rated by users *a* and *b* for each rating criterion *c*, as shown below:

$$BC^{c}_{i,j} = \sum_{h=1}^{x} \sqrt{\left(\frac{\#h}{\#i} \right) \left(\frac{\#h}{\#j} \right)} \tag{5}$$

Where *x* denotes the number of possible rating values, *#h* represents the number of users who rated an item with value *h*, and *#i* and *#j* represent the total number of users who rated items *i* and *j*, respectively. This formula calculates the similarity based on the distribution of ratings across users, providing a more comprehensive measure in sparse datasets. Then, the worst-case similarity is adopted again as an aggregation function to calculate the overall similarity score between given items as follows:

$$BC(i, j) = \min_{c=1,\ldots,k} BC^{c}_{i,j} \tag{6}$$

$loc(r_{a,i}, r_{b,i})$ denotes the local similarity between two ratings, as depicted by the following formula:

$$loc(r_{a,i}, r_{b,i}) = \frac{(r_{a,i}, r_{med})(r_{b,i}, r_{med})}{\sqrt{\sum_{s \in I} (r_{a,s}, r_{med})^2} \sqrt{\sum_{s \in J} (r_{b,s}, r_{med})^2}} \tag{7}$$

Here, r_{med} is the median rating value, which is 3 in our case. This equation measures the local similarity between two ratings based on their deviation from the median rating value.

Given that both $Sim_{a,b}^{ADF}$ and $Sim_{a,b}^{BH}$ are already normalized within the range [0, 1], the standard sigmoid function can be used to directly combine them into a single score. This consolidated score will also adhere to the desired normalization range of [0, 1], as demonstrated in Equation (9).

Moreover, individual users may demonstrate varied rating behavior, with some consistently giving high ratings while others lean towards lower values. Our approach incorporates a rating preference factor (Pan et al., 2020) to address the inherent subjectivity, which represents the typical rating behavior of each user. The mean and variance of a user's ratings are used to compute the similarity between users *a* and *b*. The approach is designed to achieve a more objective similarity measure by taking into account the user's underlying rating tendencies.

$$RP_{a,b} = \frac{1}{(1+|\sigma_a - \sigma_b|)\times(1+|\mu_a - \mu_b|)} \tag{8}$$

Where $|\mu_a - \mu_b|$ represents the absolute difference between the average ratings of users *a* and *b*, $|\sigma_a - \sigma_b|$ represents the absolute difference between their respective standard variances. The values are integrated into the formula above to account for the impact of user preferences on their similarity score. A smaller value signifies the reduced influence of individual user preferences on their overall similarity, indicating a more significant emphasis on the actual content of their ratings. This formula accounts for the absolute differences in both the average and variance of ratings between users, integrating them to adjust the similarity score by reducing the influence of individual rating biases.

In conclusion, the user-based MC similarity between any two users, *a* and *b*, can be expressed as follows:

$$Sim_{a,b} = \frac{1}{(1+\exp(-(Sim_{a,b}^{ADF} + Sim_{a,b}^{BH})))} \times RP_{a,b} \tag{9}$$

Step 3: Generate predicted ratings

The mean-centering approach (Resnick et al., 1994) is utilized to derive the predicted rating of target item *i* for user *a* in this component, as depicted below:

$$P_{a,i}^{MC-CF} = \overline{r}_a + \frac{\sum_{b\in NN} Sim_{a,b} \times (r_{b,i} - \overline{r}_b)}{\sum_{b\in NN} Sim_{a,b}} \tag{10}$$

where, $\overline{r}_a$ and $\overline{r}_b$ represent the average ratings of users *a* and *b*, respectively. $r_{b,i}$ represents the rating given by user *b* to target item i. *NN* stands for the number of nearest neighbors considered for user *a*. This equation predicts the rating by adjusting the average rating of the active user based on the weighted sum of deviations from the neighbors' average ratings.

The User-based Multi-Criteria Trust Filtering Component

This component employs a two-step approach to compute the user-based MC implicit trust score for each user pair. Initially, implicit trust values are derived from user ratings to form the initial implicit trust network. Subsequently, this network helps spread indirect implicit trust among users who are not connected.

Step 1: Compute the direct trust score between connected users

This study defines a user's "trustworthiness" as their reliability in providing accurate recommendations to others, building on previous findings that indicate a strong connection between user similarity and trust in online communities. Consequently, a user's trustworthiness can be measured by evaluating the accuracy of their past recommendations for the active user (Lu et al., 2020).

Implicit trust is defined as the similarity between users' interest in shared items, based on the premise that trust often originates from shared interests and preferences. Computing the "direct implicit trust" of each user pair involves evaluating their historical ratings and measuring the prediction accuracy of one user as a recommender for another. Users *a* and *b* would receive a high implicit trust score if user *b* consistently delivers accurate predicted ratings to the user *a* based on their past ratings (Shambour et al., 2021).

In order to accomplish this task, the prediction method introduced by Resnick et al. (1994) is initially utilized to calculate the predicted ratings for each pair of users, as illustrated below:

$$P_{a,i} = \overline{r}_a + (U^b(i) - \overline{r}_b) \tag{11}$$

This equation computes the predicted rating of user *a* for item *i* by adjusting the user's average rating $\overline{r}_a$ based on the deviation of the user *b*'s overall rating from his average rating $\overline{r}_b$.

Following the prediction, the Manhattan Distance similarity measure (Adomavicius & Kwon, 2007; Bilge & Kaleli, 2014) is used to compute the user-based distance among users *a* and *b* as presented below:

$$MD_{a,b} = \sum_{i=1}^{n} abs(P_{a,i} - U^b(i)) \tag{12}$$

where $P_{a,i}$ denotes the predicted rating of user *a* on item *i*, and *n* covers all items that both users have rated in common. This formula sums the absolute differences between predicted and overall ratings for co-rated items. To ensure values fall within the range [0, 1], the Max-Min normalization method (Han & Kamber, 2006) is applied to both predicted and overall utility ratings. Intuitively, smaller distances between users indicate greater direct implicit trust. Therefore, the following metric is used to convert the calculated distance into a direct implicit trust score:

$$Trust_{a,b} = \frac{1}{1 + MD_{a,b}} \tag{13}$$

This formula normalizes the Manhattan distance to a [0, 1] range, where a smaller distance indicates a higher trust score.

Manhattan distance metric takes into account only the absolute difference in ratings between users, without considering the percentage of items that are commonly rated. This can lead to inflated trust scores for users with limited shared items, potentially hindering accuracy. The Relevant Jaccard method (Bag et al., 2019) is utilized as a structural similarity measure to tackle this issue. The Relevant Jaccard method is calculated as follows:

$$RJacc_{a,b} = \frac{1}{1 + \left(\frac{1}{|I_a \cap I_b|}\right) + \left(\frac{|I_a| - |I_a \cap I_b|}{1 + |I_a| - |I_a \cap I_b|}\right) + \left(\frac{1}{1 + |I_b| - |I_a \cap I_b|}\right)} \tag{14}$$

where $|I_a|$ and $|I_b|$ represent the total number of items that users *a* and *b* have rated, respectively. $|I_a \cap I_b|$ represents the total number of items that both users *a* and *b* have rated in common. This formula calculates the proportion of shared items relative to the union of their rated items.

Finally, the User-based Multi-Criteria direct trust between users *a* and *b* can be expressed as follows:

$$Trust_{a,b}^{Direct} = Trust_{a,b} \times RJacc_{a,b} \tag{15}$$

This formula combines both the trust score and the Relevant Jaccard similarity metrics to provide a comprehensive measure of direct trust.

Step 2: Propagating trust for unconnected users

The initial direct trust network, created based on the calculated trust scores in Step 1, may remain sparse because users usually provide a limited number of ratings in recommender system applications. To overcome this sparsity and maximize the network's utility, our approach adopts trust propagation, a concept observed in social networks. This allows trust to be transmitted through through intermediary users, thereby establishing new indirect connections within the network. The process involves expanding the network and enabling more intricate trust relationships between users that go beyond direct interactions.

To address the challenge of sparsity within the implicit trust network, we propose an aggregation function that incorporates confidence weights when measuring trust propagated between users. The function evaluates the level of implicit trust from user *a* to user *c* via user *b*. For any users *a*,*b*,*c* in the implicit trust network *G*, the propagated trust score is calculated as follows:

$$Trust_{a,c}^{Prop} = \frac{\sum_{b \in intermediary(a\ and\ c)} \left(Trust_{a,b}^{Direct} \times RJacc_{a,b}\right) + \left(Trust_{b,c}^{Direct} \times RJacc_{b,c}\right)}{\sum_{b \in intermediary(a\ and\ c)} RJacc_{a,b} + RJacc_{b,c}} \tag{16}$$

where user *b* serves as a common neighbour to users *a* and *c*. This formula calculates the maximum trust score that can be propagated from *a* to *c* through any intermediary user *b*.

In summary, our approach first calculates the direct implicit trust between directly linked users (sharing similar items) using Equation (15). Then, it utilizes Equation (16) to propagate trust between non-connected users through intermediary users, enriching the network with valuable connections.

Step 3: Compute global trust scores for users

The global trust score of users plays a crucial role in enhancing the system's capability to predict ratings for unobserved items, particularly when an active user lacks sufficient nearest neighbors. As highlighted in (Song et al., 2017), this score is computed based on two key factors:

- Average rating deviation: This aspect captures the user's tendency to deviate from the average ratings of items they have rated. It is calculated as the average difference between the user's rating and the average rating for each item. A smaller deviation indicates higher user conformity and potentially greater trustworthiness.
- Connectivity in trust network: This factor reflects the user's overall level of engagement within the implicit trust network, considering the number of trust relationships they have with other users.

The formula for calculating the global trust score is shown below:

$$GTS_a = \exp\left(-\frac{\sum_{i \in I_a} \left|r_{a,i} - \overline{r_i}\right|}{\left|I_a\right|}\right) \times \sqrt{\frac{\left|U_a\right|}{\left|U\right|}} \tag{17}$$

where $r_{a,i}$ represents the rating of user *a* given to item *i*, $\overline{r_i}$ denotes the mean rating of item *i*, and $\left|U_a\right|$ is the number of users connected to user *a* within the implicit trust network. This formula combines the average rating deviation and connectivity to compute a global trust score.

Step 4: Generate predicted ratings

Using the mean centering approach (Resnick et al., 1994) once more, we calculate the predicted rating of target item *i* for the active user *a* in this component, as shown below:

$$P_{a,i}^{MC-Trust} = \begin{cases} \overline{r}_a + \dfrac{\sum_{b\in NN} Trust_{a,b} \times (r_{b,i} - \overline{r}_b)}{\sum_{b\in NN} Trust_{a,b}} & \text{if } Trust_{a,b} \neq 0 \\ \overline{r}_a + \dfrac{\sum_{b\in NN} GTS_b \times (r_{b,i} - \overline{r}_b)}{\sum_{b\in NN} GTS_b} & \text{if } Trust_{a,b} = 0 \end{cases} \qquad (18)$$

The Fusion Recommendation Component

Building on the success of fusing diverse recommendation techniques in prior work, this component leverages a "switch hybridization" scheme (Burke, 2007). This scheme dynamically selects the most suitable recommendation approach based on specific conditions, ultimately aiming to improve recommendation accuracy. The key criterion for selecting the recommendation approach is its capacity to predict ratings for items that have not been previously seen. If both approaches under consideration can provide such predictions, the Root Mean Square metric is employed to combine their outputs. This metric offers the advantage of quantifying the overall agreement or disagreement between the two ratings, providing a basis for informed decision-making.

$$P_{a,i}^{Final} = \begin{cases} 0 & ; \text{ if } P_{a,i}^{MC-CF} = 0 \text{ and } P_{a,i}^{MC-Trust} = 0 \\ P_{a,i}^{MC-CF} & ; \text{ if } P_{a,i}^{MC-CF} \neq 0 \text{ and } P_{a,i}^{MC-Trust} = 0 \\ P_{a,i}^{MC-Trust} & ; \text{ if } P_{a,i}^{MC-CF} = 0 \text{ and } P_{a,i}^{MC-Trust} \neq 0 \\ \sqrt{\dfrac{(P_{a,i}^{MC-CF})^2 + (P_{a,i}^{MC-Trust})^2}{2}} & ; \text{ if } P_{a,i}^{MC-CF} \neq 0 \text{ and } P_{a,i}^{MC-Trust} \neq 0 \end{cases} \qquad (19)$$

EXPERIMENTS

The following section explores the experimental evaluation of the UMCTCF approach proposed in this study. The benchmark datasets utilized are presented, and the key results are analyzed, with a comparison of UMCTCF's performance against established baseline methods using relevant evaluation metrics.

DATASETS AND EVALUATION MEASURES

Our experimental evaluation leverages two multi-criteria tourism datasets namely Restaurants-TripAdvisor and the Hotels-TripAdvisor (Jannach et al., 2014). Table 2 summarizes their key characteristics, including the number of users, items, ratings, criteria, and rating scale.

Table 2. Datasets properties

Name	Users	Items	# of ratings	# of criteria	Rating scale
Restaurants	1254	205	14633	3	[1,5]
Hotels	1039	693	28829	7	[1,5]

To assess how sparsity affects our proposed UMCTCF method and other baseline recommendation methods, we generated six datasets with different degrees of sparsity. Ratings were deleted randomly from the original dataset, leading to sparsity levels ranging from 98.0% to 99.8%. Sparsity is determined by subtracting dataset density from 1, where density represents the ratio of non-zero entries (total ratings) to all possible entries (users multiplied by items). Additionally, we created six datasets to evaluate how UMCTCF and baseline recommendation methods perform when encountering new users. Each dataset allocated numbers of ratings to new users ranging from 10 to 20 ratings. This setup allows us to examine how the methods handle users who have limited ratings.

To assess the performance of our proposed approach and benchmark methods, we employ three key evaluation metrics: Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Coverage. MAE and RMSE help us understand the difference between predicted user ratings and actual ratings, showing how accurately the predictions match what users truly prefer. Lower values of both MAE and RMSE indicate better predictive accuracy. While both metrics focus on predictive accuracy, RMSE offers insights by prioritizing the correction of prediction errors. This can be especially useful in situations where significant deviations have an impact on user satisfaction or system performance. Furthermore, Coverage plays a crucial role in evaluating recommender systems, particularly when addressing sparsity and new user challenges. It measures the proportion of items for which the method can generate predictions. A higher coverage value indicates the ability to recommend a wider range of items, potentially even with limited user-item interactions, leading to more diverse and satisfying recommendations for users. This is particularly beneficial for new users with few ratings, as the system can still suggest relevant items based on available information (Aggarwal, 2016a).

BASELINE METHODS

To conduct a comprehensive evaluation of our proposed UMCTCF approach, we compared its performance against three established CF-based recommendation methods:

- The MC User-based CF (MC-UCF): This method exploits multi-criteria ratings between users to boost prediction accuracy (Adomavicius & Kwon, 2007).
- The MC User-based Trust-enhanced CF (MC-TeCF): This method combines multi-criteria ratings with implicit trust relationships between users (Shambour, 2016).
- The MC User-based CF (MC-MDCF): This method incorporates multi-criteria ratings and employs the Mahalanobis distance metric to deliver accurate recommendations (Wasid & Ali, 2018).

COMPARISON RESULTS

The proposed UMCTCF recommendation approach undergoes several experiments to confirm its enhancements in prediction accuracy and coverage in comparison with baseline methods. These experiments were designed to tackle the issues presented by sparsity and new users across the presented datasets.

Analysis of prediction accuracy performance utilizing the Restaurants dataset

The proposed UMCTCF approach demonstrates outstanding performance in the Restaurants dataset, consistently outperforming baseline methods that include MC-UCF, MC-TeCF, and MC-MDCF in terms of prediction accuracy. This is evident in Figures 2 and 3, which illustrate the performance across varying numbers of nearest neighbors ranging from 5 to 50. On average, UMCTCF outperforms the baselines by approximately 15% in MAE and 19% in RMSE compared to MC-UCF, 3% and 1% compared to MC-TeCF, and 8% and 5% compared to MC-MDCF. Notably, both MAE and RMSE decrease consistently with increasing neighbor sizes, achieving their optimal performance with the 50 nearest neighbors. In essence, these results convincingly demonstrate that UMCTCF outperforms existing methods in terms of prediction accuracy, highlighting its potential for enhanced recommendation effectiveness.

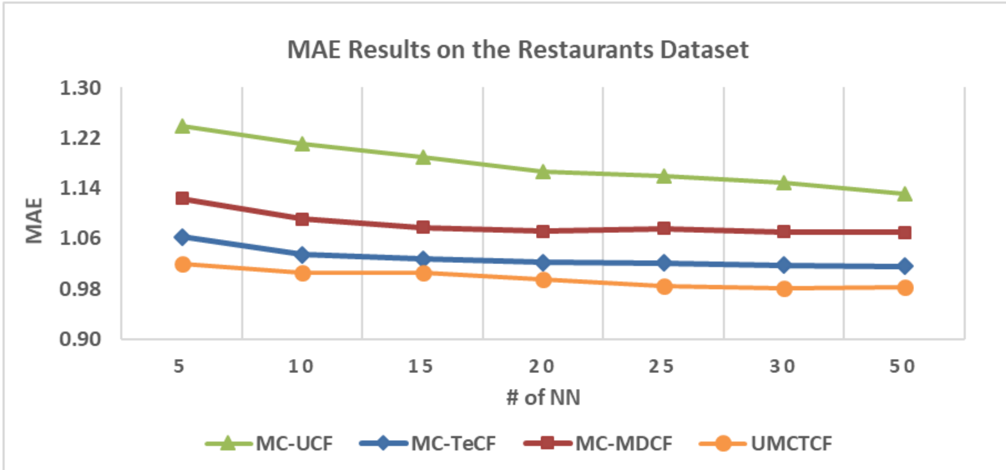

Figure 2. Prediction accuracy (MAE) evaluation results on the Restaurant dataset

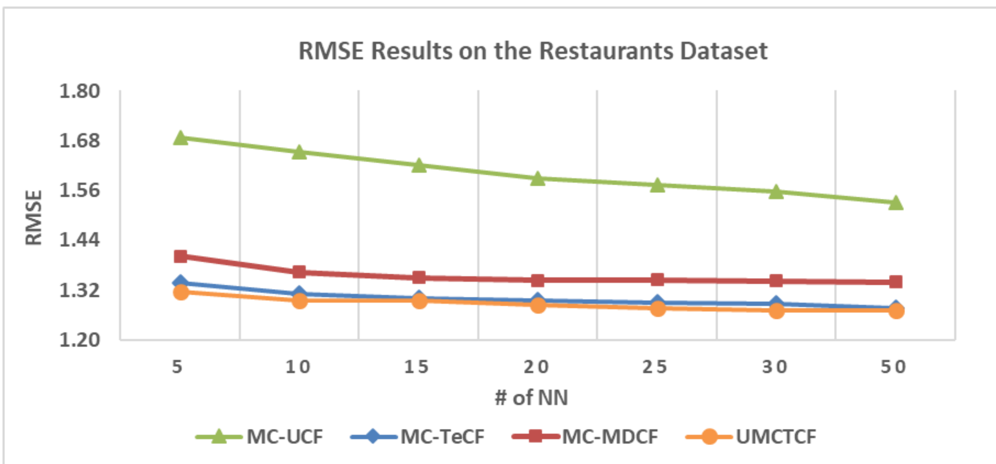

Figure 3. Prediction accuracy (RMSE) evaluation results on the Restaurant dataset

Analysis of prediction accuracy performance utilizing the Hotels dataset

The proposed UMCTCF approach shows exceptional results in the Hotels dataset, consistently exceeding the prediction accuracy of baseline methods, including MC-UCF, MC-TeCF, and MC-MDCF. This dominance is visually depicted in Figures 4 and 5, showcasing performance across various nearest-neighbor sizes (5, 10, 15, 20, 30, and 50). Analyzing average results, UMCTCF achieves remarkable improvements: 45% reduction in both MAE and RMSE compared to MC-UCF, 15% and 8% improvement in MAE and RMSE over MC-TeCF, and 25% and 24% reduction in MAE and RMSE compared to MC-MDCF. Again, both MAE and RMSE decrease consistently with increasing neighbor sizes, reaching their peak performance at 50 neighbors.

In summary, across both Restaurants and Hotels datasets, the UMCTCF is a more effective recommendation method compared to the baselines, particularly in terms of predicting user preferences accurately. This improved prediction accuracy has the potential to enhance the overall effectiveness of the recommendations in practice.

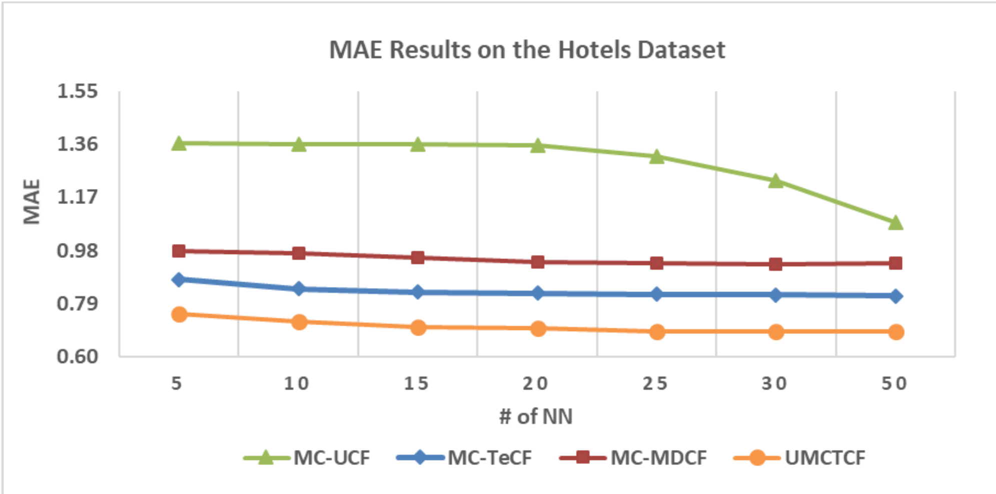

Figure 4. Prediction accuracy (MAE) evaluation results on the Hotels dataset

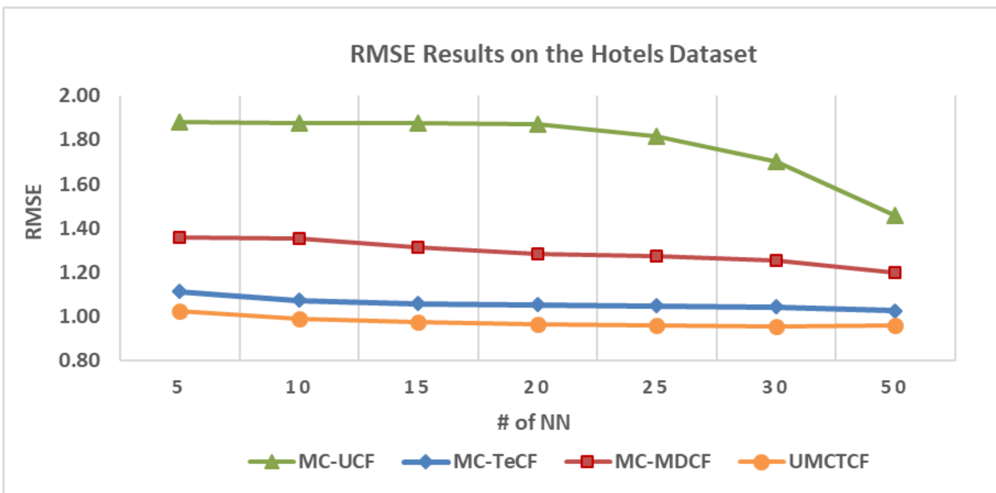

Figure 5. Prediction accuracy (RMSE) evaluation results on the Hotels dataset

Exploration of prediction accuracy and Coverage at different levels of sparsity

Figures 6 and 7 showcase the performance of our proposed UMCTCF approach compared to the MC-UCF, MC-TeCF, and MC-MDCF baselines under varying sparsity levels. The evaluation metrics employed are MAE and Coverage. On average, UMCTCF outperforms the baselines by approximately 63%, 28%, and 62% in terms of MAE. This demonstrates its superior ability to maintain prediction accuracy even with sparse data. Notably, MAE increases unsurprisingly as sparsity increases, highlighting the challenge faced by all methods. However, UMCTCF's resilience is evident, particularly in the 99.8% sparse dataset, where it achieves a 56% average improvement over baselines. Furthermore, UMCTCF also exhibits significant superiority in Coverage, achieving average improvements of 48%, 8%, and 45% over baselines. This indicates its effectiveness in recommending a wider range of items, especially in sparse datasets where other methods struggle.

Obviously, Coverage generally increases with decreasing sparsity. However, in the 99.8% sparse dataset, UMCTCF still boasts a remarkable 73% average improvement, demonstrating its robustness in recommending diverse items even with limited rating data. These remarkable results highlight the potential of UMCTCF for accurate and diverse recommendations even in challenging data sparsity conditions.

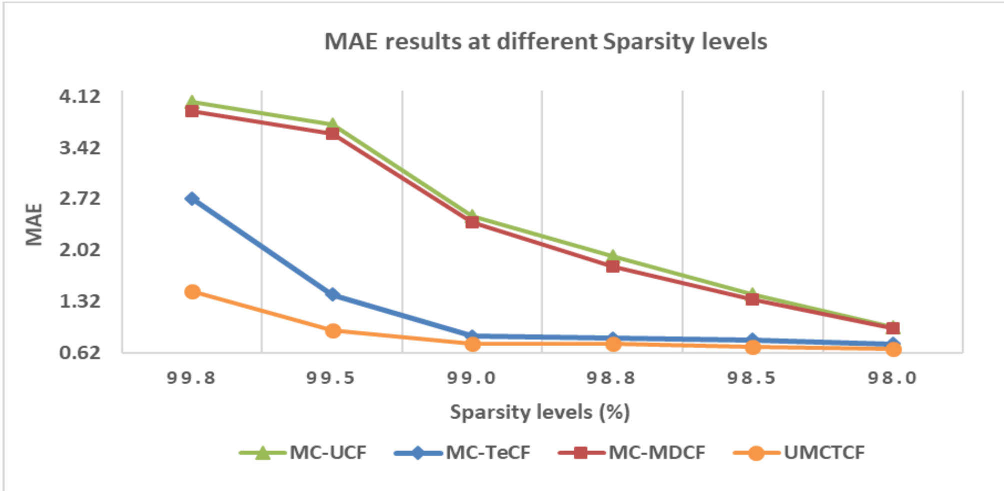

Figure 6. Prediction accuracy (MAE) evaluation results at different levels of sparsity

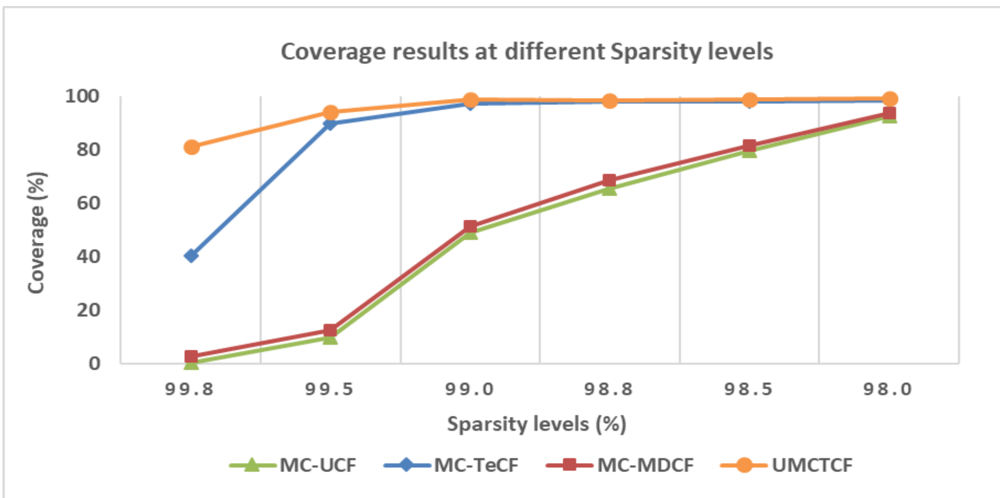

Figure 7. Prediction coverage evaluation results at different levels of sparsity

Exploration of prediction accuracy and Coverage for new users with varied numbers of ratings

Figures 8 and 9 illustrate the performance of UMCTCF in mitigating the negative impact of the new user problem on both prediction accuracy and Coverage. Compared to the MC-UCF, MC-TeCF, and MC-MDCF baselines with varying new user rating numbers, UMCTCF demonstrates consistently superior performance.

Figure 8 showcases UMCTCF's significant improvement in MAE compared to baselines, with an average of 68% over MC-UCF, 10% over MC-TeCF, and 67% over MC-MDCF. These significant improvements demonstrate UMCTCF's ability to surpass baseline methods in accurately predicting the preferences of new users, even with limited data. Figure 9 reveals UMCTCF's advantage in Coverage compared to baselines, achieving average improvements of 51% over MC-UCF, 6% over MC-TeCF, and 50% over MC-MDCF. This signifies UMCTCF's effectiveness in recommending a wider range of items to new users, potentially leading to more diverse and satisfying experiences.

As expected, MAE and the number of ratings assigned to new users show a negative correlation (decreasing with more ratings), while Coverage shows a positive correlation (increasing with more ratings). Notably, UMCTCF displays superior reliability and efficacy in both metrics compared to baselines, especially for users with very limited ratings. This is evident in the substantial improvements in both MAE and Coverage results.

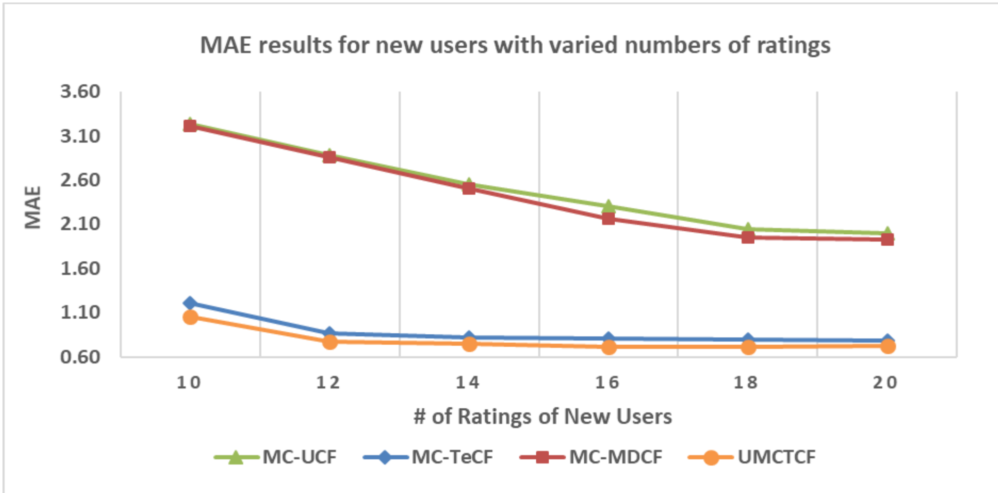

Figure 8. Prediction accuracy (MAE) evaluation results for new users with varied numbers of ratings

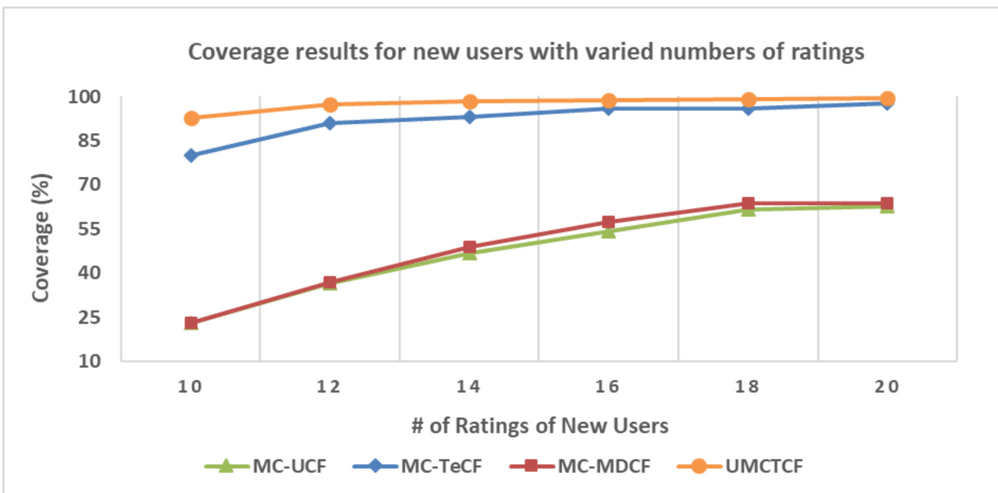

Figure 9. Prediction coverage evaluation results for new users with varied numbers of ratings

The UMCTCF approach demonstrates significant potential for enhancing user satisfaction and decision-making in the tourism domain. By leveraging detailed multi-criteria ratings and implicit trust relationships, UMCTCF delivers highly personalized and accurate recommendations, aligning closely with individual user preferences across various aspects like cleanliness, service quality, and location. This comprehensive approach results in lower prediction errors, higher recommendation coverage, and better overall performance compared to traditional methods. For tourism providers, UMCTCF offers actionable insights that can drive data-driven decision-making and optimize marketing strategies. By understanding detailed user preferences, businesses can focus on enhancing specific aspects of their services that are most valued by customers. Additionally, the integration of trust networks fosters a sense of community and reliability, building long-term customer loyalty and differentiating providers from competitors. Overall, UMCTCF not only boosts user satisfaction but also provides strategic advantages that contribute to sustained business success in the tourism sector.

A Comprehensive Assessment

The UMCTCF approach demonstrates significant potential for enhancing user satisfaction and decision-making in the tourism domain. By leveraging detailed multi-criteria ratings, implicit trust relationships, and reputation scores, UMCTCF delivers highly personalized and accurate recommendations. It closely matches the distinct preferences of users in different aspects, such as cleanliness, service quality, room quality, and location, when it comes to hotel recommendations. This comprehensive approach results in lower prediction errors, higher recommendation coverage, and better overall performance compared to traditional methods. For tourism providers, UMCTCF offers actionable insights that can drive data-driven decision-making and optimize marketing strategies. By understanding detailed user preferences, businesses can focus on enhancing specific aspects of their services that are most valued by customers. Overall, UMCTCF not only boosts user satisfaction but also provides strategic advantages that contribute to sustained business success in the tourism sector.

While UMCTCF presents notable advantages, it is crucial to acknowledge and address potential limitations. A primary concern is data availability, as acquiring multi-criteria ratings can prove challenging. Moreover, the computational requirements for processing such ratings may present scalability and real-time processing obstacles, particularly for large-scale systems. To enhance the impact and relevance of UMCTCF, practical insights can guide its implementation. Incremental improvements in data collection and optimizing computational resources are essential steps. In the tourism domain, platforms can adopt progressive strategies for collecting detailed ratings, establish data-sharing partnerships, and invest in algorithm optimization to manage complexity. Additionally, educating users on the benefits of detailed feedback can further refine the system, leading to more accurate and personalized recommendations. These initiatives not only improve user satisfaction but also provide actionable insights for tourism providers, fostering a more competitive and dynamic tourism ecosystem.

Discussion

The UMCTCF approach represents a significant advancement in personalized tourism recommendations, effectively addressing the challenges of data sparsity and the cold-start problem. Its innovative use of multi-criteria ratings, implicit trust relationships, and reputation scores enables it to consistently outperform baseline methods in terms of prediction accuracy and coverage.

In both Restaurants and Hotels datasets, UMCTCF demonstrates significant improvements in MAE and RMSE when compared to MC-UCF, MC-TeCF, and MC-MDCF. For instance, in the Restaurants dataset, UMCTCF surpasses MC-TeCF, which closely resembles our proposed approach, by achieving a 3% improvement in MAE and a 1% improvement in RMSE. These improvements are even more pronounced in the Hotels dataset, where UMCTCF outperforms MC-TeCF with a 15% improvement in MAE and an 8% improvement in RMSE.

Furthermore, the UMCTCF approach demonstrates robust performance under high sparsity conditions, with sparsity levels ranging from 98.0% to 99.8%. In a scenario with 99.8% sparsity, UMCTCF demonstrates a 56% average improvement in MAE and a 73% improvement in coverage compared to baseline methods. The approach also effectively mitigates the cold-start problem for new users, enabling reliable recommendations for new users with limited historical ratings. In a highly cold-start scenario, where a new user has only ten ratings, UMCTCF exhibits a 59% average improvement in MAE and a 55% improvement in coverage compared to baseline methods.

UMCTCF’s success stems from its incorporation of multi-criteria ratings, implicit trust relationships, and reputation scores, which expand the pool of potential neighbors during the neighbor selection phase. This leads to superior results in terms of predictive accuracy and coverage, particularly when dealing with extremely sparse datasets or new users with very few ratings. By effectively addressing the challenges of data sparsity and the cold-start problem, UMCTCF contributes to a more satisfying user experience and improved decision-making in tourism-related activities. The enhanced prediction accuracy and coverage ensure that users receive recommendations that are more closely aligned with their preferences, enhancing user satisfaction and engagement.

The UMCTCF approach represents a transformative advancement in personalized tourism recommendation systems, leading to greater customer satisfaction and loyalty for hotel and restaurant owners. This approach effectively matches customers with hotels and restaurants that closely align with their preferences, thus enhancing their overall experience and increasing the likelihood of repeat visits. Additionally, UMCTCF enables businesses to optimize marketing strategies and service offerings, ensuring that promotions and deals reach those most likely to appreciate them. Moreover, the system's capacity to effectively accommodate new users and diverse preferences ensures that even first-time visitors receive relevant recommendations, potentially converting them into regular patrons and broadening the appeal of the business.

Beyond enhancing customer experience, UMCTCF provides valuable operational insights for hotel and restaurant owners. Detailed data from multi-criteria ratings can inform business decisions, such as inventory management and staffing, based on popular facilities or menu items. This approach not only distinguishes businesses from competitors but also underscores their commitment to innovation and customer service through cutting-edge technology. Overall, UMCTCF not only benefits customers with personalized recommendations but also empowers business owners with actionable insights and a competitive advantage.

CONCLUSION

Recommender systems serve a vital role in the tourism industry as they efficiently match a wide range of tourism facilities, such as restaurants, hotels, and museums, with the interests of individual travelers. By using data and personalized recommendations, these systems enable travelers to explore available choices and create a customized travel experience based on their particular preferences. This research proposed a novel User-based Multi-Criteria Trust-aware Collaborative Filtering (UMCTCF) approach for personalized tourism recommendations. The proposed approach effectively integrates multi-criteria user preferences and implicit trust networks to enhance recommendation accuracy and coverage. A comprehensive experimental evaluation was conducted using two real-world tourism datasets (Restaurants-TripAdvisor and Hotels-TripAdvisor) with varying levels of data sparsity and new user scenarios.

Our findings demonstrate that the UMCTCF approach consistently outperforms the baseline recommendation methods in terms of prediction accuracy, as measured by MAE and RMSE, and coverage. Significantly, the UMCTCF exhibits exceptional robustness in sparse conditions, maintaining superior accuracy and coverage even with limited historical ratings. Additionally, UMCTCF effectively addresses the new user problem, delivering accurate and diverse recommendations to users with limited historical ratings. These results highlight the effectiveness of our approach in understanding user preferences and delivering meaningful recommendations, particularly in challenging scenarios.

The enhanced performance of UMCTCF signifies the importance of incorporating multi-criteria analysis and trust-based filtering into tourism recommender systems. By considering diverse aspects of user preferences and utilizing the implicit trust between users, the proposed approach yields more accurate and diverse recommendations. This has direct implications for improving user satisfaction and decision-making in the context of e-tourism.

In light of these findings, the UMCTCF approach offers significant practical implications for all stakeholders in the tourism industry. For travelers, UMCTCF translates into a more personalized and enjoyable travel experience, where recommendations closely align with their preferences, leading to increased satisfaction and loyalty. For tourism businesses, particularly restaurants and hotels, UMCTCF offers opportunities to better understand and cater to customer preferences, thereby enhancing customer retention, improved operational efficiency, and competitive advantage. Additionally, for technology providers and researchers, UMCTCF presents an avenue for innovation and further advancement in personalized recommendation systems with potential applications beyond the tourism industry. By effectively addressing the needs of all stakeholders, UMCTCF has the potential to revolutionize the tourism industry and create a more personalized and enriching experience for everyone involved.

Future research avenues could explore several promising paths to further enrich the UMCTCF approach and broaden its applicability. One avenue involves the integration of contextual information, such as spatial or location-based data, to provide deeper insights into user preferences and enhance the accuracy and relevance of recommendations. For instance, considering factors like the user's current location, travel plans, and time constraints could lead to more personalized and timely suggestions. Another potential direction entails leveraging user-generated content, including reviews and social media posts, to glean valuable insights into user preferences and sentiments. Analyzing this content can refine the understanding of user preferences beyond explicit ratings, thereby enhancing recommendation personalization. Additionally, investigating cross-domain applications of UMCTCF in various e-commerce sectors beyond tourism holds promise for personalized recommendation research. By applying multi-criteria analysis and trust-based filtering principles to domains like online shopping, entertainment, and healthcare, researchers can unlock new insights and contribute to the development of more effective recommendation systems. Furthermore, exploring how optimization algorithms could be integrated with UMCTCF to potentially enhance both recommendation accuracy and efficiency presents a valuable area for future investigation.

REFERENCES

Adomavicius, G., & Kwon, Y. O. (2007). New recommendation techniques for multicriteria rating systems. *IEEE Intelligent Systems*, *22*(3), 48-55. https://doi.org/10.1109/MIS.2007.58

Aggarwal, C. C. (2016a). Evaluating recommender systems. *Recommender systems: The textbook* (pp. 225-254). Springer. https://doi.org/10.1007/978-3-319-29659-3_7

Aggarwal, C. C. (2016b). Neighborhood-based collaborative filtering. *Recommender systems: The textbook* (pp. 29-70). Springer. https://doi.org/10.1007/978-3-319-29659-3_2

Ahmadian, S., Joorabloo, N., Jalili, M., Ren, Y., Meghdadi, M., & Afsharchi, M. (2020). A social recommender system based on reliable implicit relationships. *Knowledge-Based Systems*, *192*, 105371. https://doi.org/10.1016/j.knosys.2019.105371

Asani, E., Vahdat-Nejad, H., & Sadri, J. (2021). Restaurant recommender system based on sentiment analysis. *Machine Learning with Applications*, *6*, 100114. https://doi.org/10.1016/j.mlwa.2021.100114

Bag, S., Kumar, S. K., & Tiwari, M. K. (2019). An efficient recommendation generation using relevant Jaccard similarity. *Information Sciences*, *483*, 53-64. https://doi.org/10.1016/j.ins.2019.01.023

Bilge, A., & Kaleli, C. (2014, May). A multi-criteria item-based collaborative filtering framework. *Proceedings of the 11th International Joint Conference on Computer Science and Software Engineering*, *Chon Buri*, 18-22. https://doi.org/10.1109/JCSSE.2014.6841835

Burke, R. (2007). Hybrid web recommender systems. In P. Brusilovsky, A. Kobsa, & W. Nejdl (Eds.), *The adaptive web: Methods and strategies of web personalization* (pp. 377-408). Springer. https://doi.org/10.1007/978-3-540-72079-9_12

Camacho, L. A. G., & Alves-Souza, S. N. (2018). Social network data to alleviate cold-start in recommender system: A systematic review. *Information Processing & Management*, *54*(4), 529-544. https://doi.org/10.1016/j.ipm.2018.03.004

Chalkiadakis, G., Ziogas, I., Koutsmanis, M., Streviniotis, E., Panagiotakis, C., & Papadakis, H. (2023). A novel hybrid recommender system for the tourism domain. *Algorithms*, *16*(4), 215. https://doi.org/10.3390/a16040215

Chaudhari, K., & Thakkar, A. (2020). A comprehensive survey on travel recommender systems. *Archives of Computational Methods in Engineering*, *27*(5), 1545-1571. https://doi.org/10.1007/s11831-019-09363-7

Cui, C., Wei, M., Che, L., Wu, S., & Wang, E. (2022). Hotel recommendation algorithms based on online reviews and probabilistic linguistic term sets. *Expert Systems with Applications*, *210*, 118503. https://doi.org/10.1016/j.eswa.2022.118503

Dyer, J. S. (2005). Maut – Multiattribute utility theory. In J. Figueira, S. Greco, & M. Ehrgott (Eds.), *Multiple criteria decision analysis: State of the art surveys* (pp. 265-292). Springer. https://doi.org/10.1007/0-387-23081-5_7

Esmaeili, L., Mardani, S., Golpayegani, S. A. H., & Madar, Z. Z. (2020). A novel tourism recommender system in the context of social commerce. *Expert Systems with Applications*, *149*, 113301. https://doi.org/10.1016/j.eswa.2020.113301

Ganji, R. N., Dadkhah, C., & Tohidi, N. (2023). Improving sentiment classification for hotel recommender system through deep learning and data balancing. *Computación y Sistemas*, *27*(3), 811-825. https://doi.org/10.13053/cys-27-3-4655

Gazdar, A., & Hidri, L. (2020). A new similarity measure for collaborative filtering based recommender systems. *Knowledge-Based Systems*, *188*, 105058. https://doi.org/10.1016/j.knosys.2019.105058

Han, J., & Kamber, M. (2006). *Data mining: Concepts and techniques* (2nd ed.). Morgan Kaufmann.

Hartanto, M., & Utama, D. N. (2020). Intelligent decision support model for recommending restaurant. *Cogent Engineering*, *7*(1), Article 1763888. https://doi.org/10.1080/23311916.2020.1763888

Hassan, A. K. A., & Abdulwahhab, A. B. A. (2019). Location aspect based sentiment analyzer for hotel recommender system. *Iraqi Journal of Science*, *60*(1), 143-156.

Hong, M., & Jung, J. J. (2021). Multi-criteria tensor model for tourism recommender systems. *Expert Systems with Applications*, *170*, 114537. https://doi.org/10.1016/j.eswa.2020.114537

Jannach, D., Zanker, M., & Fuchs, M. (2014). Leveraging multi-criteria customer feedback for satisfaction analysis and improved recommendations. *Information Technology & Tourism*, *14*(2), 119-149. https://doi.org/10.1007/s40558-014-0010-z

Ko, H., Lee, S., Park, Y., & Choi, A. (2022). A survey of recommendation systems: recommendation models, techniques, and application fields. *Electronics*, *11*(1), 1-48. https://doi.org/10.3390/electronics11010141

Kulkarni, A., Barve, P., & Phade, A. (2019). A machine learning approach to building a tourism recommendation system using sentiment analysis. *International Journal of Computer Applications*, *178*, 48-51. https://doi.org/10.5120/ijca2019919031

Lu, J., Zhang, Q., & Zhang, G. (2020). *Recommender systems: Advanced Developments*. World Scientific. https://doi.org/10.1142/11947

Maru'ao, M. S. P., & Suharjito. (2021). Tourism recommender system using hybrid multi-criteria approach. *IOP Conference Series: Earth and Environmental Science*, *729*(1), 012118. https://doi.org/10.1088/1755-1315/729/1/012118

Nan, X., kanato, K., & Wang, X. (2022). Design and implementation of a personalized tourism recommendation system based on the data mining and collaborative filtering algorithm. *Computational Intelligence and Neuroscience*, *2022*, Article 1424097. https://doi.org/10.1155/2022/1424097

Pan, R., Ge, C., Zhang, L., Zhao, W., & Shao, X. (2020). A new similarity model based on collaborative filtering for new user cold start recommendation. *IEICE Transactions on Information and Systems*, *103*(6), 1388-1394. https://doi.org/10.1587/transinf.2019EDP7258

Patra, B. K., Launonen, R., Ollikainen, V., & Nandi, S. (2015). A new similarity measure using Bhattacharyya coefficient for collaborative filtering in sparse data. *Knowledge-Based Systems*, *82*, 163-177. https://doi.org/10.1016/j.knosys.2015.03.001

Perumal, S., Rawal, S., & Richa. (2023). Handling cold-start problem in restaurant recommender system using ontology. In A. Noor, K. Saroha, E. Pricop, A. Sen, & G. Trivedi (Eds.), *Proceedings of Emerging Trends and Technologies on Intelligent Systems Singapore* (pp. 319-329). Springer. https://doi.org/10.1007/978-981-19-4182-5_25

Ray, B., Garain, A., & Sarkar, R. (2021). An ensemble-based hotel recommender system using sentiment analysis and aspect categorization of hotel reviews. *Applied Soft Computing*, *98*, 106935. https://doi.org/10.1016/j.asoc.2020.106935

Resnick, P., Iacovou, N., Suchak, M., Bergstrom, P., & Riedl, J. (1994, October). GroupLens: An open architecture for collaborative filtering of netnews. *Proceedings of the ACM Conference on Computer Supported Cooperative Work*, *Chapel Hill, North Carolina, USA*, 175-186. https://doi.org/10.1145/192844.192905

Ricci, F. (2022). Recommender systems in tourism. In Z. Xiang, M. Fuchs, U. Gretzel, & W. Höpken (Eds.), *Handbook of e-tourism* (pp. 457-474). Springer. https://doi.org/10.1007/978-3-030-48652-5_26

Sarkar, J. L., Majumder, A., Panigrahi, C. R., Roy, S., & Pati, B. (2023). Tourism recommendation system: A survey and future research directions. *Multimedia Tools and Applications*, *82*(6), 8983-9027. https://doi.org/10.1007/s11042-022-12167-w

Savchenko, A. V. (2022, September). Recommending restaurants based on classification of photos from the gallery of mobile device. *Proceedings of the IEEE 20th Jubilee International Symposium on Intelligent Systems and Informatics*, *Subotica, Serbia*, 431-436. https://doi.org/10.1109/SISY56759.2022.10036249

Shambour, Q. Y. (2016). A user-based multi-criteria recommendation approach for personalized recommendations. *International Journal of Computer Science and Information Security*, *14*(12), 657-663.

Shambour, Q. Y., Abu-Alhaj, M. M., & Al-Tahrawi, M. M. (2020). A hybrid collaborative filtering recommendation algorithm for requirements elicitation. *International Journal of Computer Applications in Technology*, *63*(1-2), 135-146. https://doi.org/10.1504/IJCAT.2020.107908

Shambour, Q. Y., Al-Zyoud, M., Abu-Shareha, A., & Abualhaj, M. (2023). Medicine recommender system based on semantic and multi-criteria filtering. *Interdisciplinary Journal of Information, Knowledge, and Management*, *18*, 435-457. https://doi.org/10.28945/5172

Shambour, Q. Y., Hussein, A. H., Kharma, Q. M., & Abualhaj, M. M. (2022). Effective hybrid content-based collaborative filtering approach for requirements engineering. *Computer Systems Science and Engineering*, *40*(1), 113-125. https://doi.org/10.32604/CSSE.2022.017221

Shambour, Q. Y., & Lu, J. (2011, April). Integrating multi-criteria collaborative filtering and trust filtering for personalized recommender systems. *Proceedings of the IEEE Symposium on Computational Intelligence in Multicriteria Decision-Making*, *Paris, France*, 44-51. https://doi.org/10.1109/SMDCM.2011.5949274

Shambour, Q. Y., Turab, N., & Adwan, O. (2021). An effective e-commerce recommender system based on trust and semantic information. *Cybernetics and Information Technologies*, *21*(1), 103-118. https://doi.org/10.2478/cait-2021-0008

Song, H., Pei, Q., Xiao, Y., Li, Z., & Wang, Y. (2017, October). A novel recommendation model based on trust relations and item ratings in social networks. *Proceedings of the International Conference on Networking and Network Applications*, *Kathmandu, Nepal*, 17-23. https://doi.org/10.1109/NaNA.2017.17

Sun, L., Guo, J., & Zhu, Y. (2019). Applying uncertainty theory into the restaurant recommender system based on sentiment analysis of online Chinese reviews. *World Wide Web*, *22*, 83-100. https://doi.org/10.1007/s11280-018-0533-x

Wasid, M., & Ali, R. (2018). An improved recommender system based on multi-criteria clustering approach. *Procedia Computer Science*, *131*, 93-101. https://doi.org/10.1016/j.procs.2018.04.190

Yadav, D., Maheshwari, H., & Chandra, U. (2020). An approach towards hotel recommender system. *Journal of Computational and Theoretical Nanoscience*, *17*(6), 2605-2612. https://doi.org/10.1166/jctn.2020.8936

AUTHORS

Qusai Yousef Shambour earned his B.Sc. in Computer Science from Yarmouk University, Jordan, in 2001, his M.Sc. in Computer Networks from the University of Western Sydney, Australia, in 2003, and his Ph.D. in Software Engineering from the University of Technology Sydney, Australia, in 2012. Currently, he is a Professor at the Department of Software Engineering at Al-Ahliyya Amman University, Jordan. His research interests include information filtering, recommender systems, VoIP, machine learning, and data science.

Mosleh Abualhaj is a senior lecturer at Al-Ahliyya Amman University. He received his first degree in Computer Science from Philadelphia University, Jordan, in July 2004, his Master's degree in Computer Information Systems from the Arab Academy for Banking and Financial Sciences, Jordan, in July 2007, and his Doctorate in Multimedia Networks Protocols from Universiti Sains Malaysia in 2011. His research areas of interest include machine learning, VoIP, multimedia networking, and congestion control.

Ahmad Adel Abu-Shareha received his first degree in Computer Science from Al Al-Bayt University (AABU), Jordan, in 2004, his Master's degree from Universiti Sains Malaysia (USM) in Malaysia, 2006, and his Ph.D. degree from Universiti Sains Malaysia (USM) in Malaysia, 2012. His research focuses on data mining, artificial intelligence, and multimedia security. He investigated many supervised and unsupervised machine learning algorithms and employed artificial intelligence in various fields, such as computer networks, medical information processing, knowledge construction, and extraction.

Qasem Kharma received a Ph.D. in Computer Science from Florida International University in 2005. He is a Professor in the Software Engineering Department at Al-Ahliyya Amman University. His research interests are information systems, software engineering, databases, and using technology in education. He worked as a director of the E-Learning Center and Chairman of the Computer Science Department. Currently, he is the Dean of the Faculty of Information Technology.