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Title

> **A Hybrid Approach for Improving Recommendation Systems**

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ملخص

أصبحت أنظمة التوصية شائعة الاستخدام على شبكة الإنترنت. ففي معظم منصات التجارة الإلكترونية والخدمات الرقمية، يواجه المستخدمون بشكل متكرر اقتراحات من قبيل: 'العملاء الذين أحبوا هذا المنتج أحبوا أيضاً ذاكْ. والهدف الأساسي من هذه الأنظمة هو تخصيص تجربة التصفح، تحسين معدل التحويل (من زائر إلى عميل)، وتسهيل استرجاع المعلومات ذات الصلة من بين الكم الهائل من البيانات. ومع ذلك، وعلى الرغم من فعاليتها، تواجه أنظمة التوصية عدة تحديات: (١) نقص البيانات المكيّفة فعلياً مع احتياجات المستخدمين الخاصة، (٢) تشتت المستخدم أثناء عملية البحث مما يؤدي إلى ضعف الكفاءة، و(٣) صعوبة استغلال ثراء البيانات متعددة الوسائط المجمعة من مصادر متنوعة مثل شبكات التواصل الاجتماعي، المراجعات، سجلات التفاعل، والمعلومات السياقية. وقد حاولت الأبحاث الحديثة معالجة هذه الإشكالات من خلال دمج تقنيات التعلّم الآلي والتعلّم العميق، إضافة إلى أساليب اتخاذ القرار متعددة المعايير، بهدف فهم أفضل لتفضيلات المستخدمين، وسياقاتهم، والعوامل الخارجية المؤثرة.

ولتجاوز هذه القيود، نقترح في هذا العمل نظامي توصية متكاملين. الأول هو المستشار الذكي للأطعمة والمطاعم ، الذي يوظّف أساليب اتخاذ القرار متعددة المعايير لدعم خيارات غذائية أكثر صحة وشخصنة. وعلى عكس الأساليب التقليدية التي تهمل الأبعاد الغذائية ونمط الحياة، يقوم هذا النظام بدمج ملفات المستخدمين المثرية بالاحتياجات الغذائية، التفضيلات، والبيانات الجغرافية لتقديم توصيات سياقية دقيقة. يقوم نظامنا بتقييم وترتيب خيارات الطعام والمطاعم بناءً على عناصر مثل التغذية، المكونات، والملاءمة السياقية، مما يمكّن المستخدمين من اتخاذ قرارات مستنيرة تحقق توازناً بين المذاق والأهداف الصحية.

أما النظام الثاني فهو مقاربة مبتكرة للتوصية متعددة الوسائط، تستغل مصادر البيانات المتباينة (تفضيلات المستخدم، السياق الزمكاني والعاطفي) وتستعين بالشبكات العصبية الرسومية لنمذجة العلاقات المعقدة بين المستخدمين، العناصر، والعوامل السياقية. إضافة إلى ذلكَ، نقدم آلية توصية متعددة القوائم، صُمّمت لتوفير عدة قوائم مخصّصة من الاقتراحات استناداً إلى معايير مختلفة (الملاءمة، التنوع، السياق)، مما يعزز من درجة التخصيص ويحدّ من تشتت المستخدم.

الكلمات المفتاحية: أنظمة التوصية، البيانات متعددة الوسائط، الشبكات العصبية البيانية، التوصيات متعددة القوائم، اتخاذ القرار متعدّد المعايير

RÉSUMÉ

Les systèmes de recommandation sont devenus omniprésents sur Internet. Sur la plupart des plateformes de commerce électronique et de services numériques, les utilisateurs rencontrent fréquemment des suggestions du type : « les clients qui ont aimé ce produit ont également aimé celui-ci ». L'objectif principal de ces systèmes est de personnaliser l'expérience de navigation, d'optimiser le taux de conversion (visiteur → client) et de faciliter la recherche d'informations pertinentes au sein d'énormes volumes de données. Cependant, malgré leur efficacité, les systèmes de recommandation font face à plusieurs défis : (1) l'insuffisance de données réellement adaptées aux besoins spécifiques des utilisateurs, (2) la désorientation des utilisateurs lors du processus de recherche, entraînant une perte d'efficacité, et (3) la difficulté à exploiter la richesse des données multimodales collectées auprès de sources diverses telles que les réseaux sociaux, les avis, les historiques d'interactions et les informations contextuelles. Des travaux récents ont tenté de répondre à ces problématiques en intégrant des techniques d'apprentissage automatique et d'apprentissage profond, ainsi que des méthodes d'aide à la décision multicritères, afin de mieux saisir les préférences des utilisateurs, leur contexte et les facteurs externes.

Pour surmonter ces limitations, nous proposons dans ce travail deux systèmes de recommandation complémentaires. Le premier, le Smart Food and Restaurant Advisor (SFRA), repose sur les méthodes d'aide à la décision multicritères (MCDM) afin de soutenir des choix alimentaires plus sains et personnalisés. Contrairement aux approches traditionnelles qui négligent les dimensions nutritionnelles et liées au mode de vie, SFRA intègre les profils utilisateurs enrichis par les besoins alimentaires, les préférences et les données géographiques, afin de fournir des recommandations contextuelles. Notre système évalue et classe les options alimentaires et les restaurants en tenant compte de la nutrition, des ingrédients et de la pertinence contextuelle, permettant ainsi aux utilisateurs de prendre des décisions éclairées conciliant goût et objectifs de santé.

Le second système constitue une approche innovante de recommandation multimodale, exploitant des sources de données hétérogènes (préférences des utilisateurs, contexte spatio-temporel et émotionnel) et s'appuyant sur les réseaux de neurones graphiques (GNNs) pour modéliser les

relations complexes entre utilisateurs, éléments et facteurs contextuels. En outre, nous introduisons un mécanisme de recommandation multi-listes, conçu pour fournir plusieurs listes personnalisées de suggestions selon différents critères (pertinence, diversité, contexte), renforçant ainsi la personnalisation tout en réduisant la désorientation des utilisateurs.

Mots-clés : Systèmes de recommandation, Données multimodales, Réseaux de neurones graphiques (GNN), Multi-liste de recommandations, Prise de décision multicritère

ABSTRACT

Recommender systems have become ubiquitous on the internet. On most e-commerce and digital service platforms, users frequently encounter suggestions such as "customers who liked this product also liked that one." The primary goal of these systems is to personalize the browsing experience, optimize the conversion rate (visitor $\rightarrow$ customer), and facilitate the retrieval of relevant information from massive volumes of data. However, despite their effectiveness, recommender systems face several challenges: (1) the lack of data truly adapted to users' specific needs, (2) user disorientation during the search process, leading to inefficiency, and (3) difficulties in leveraging the richness of multimodal data collected from diverse sources such as social networks, reviews, interaction histories, and contextual information. Recent research has attempted to address these issues by integrating machine learning and deep learning techniques, as well as multi-criteria decision-making methods, to better capture user preferences, context, and external factors.

To overcome these limitations, we propose in this work two complementary recommender systems. The first, the Smart Food and Restaurant Advisor (SFRA), employs Multi-Criteria Decision-Making (MCDM) methods to support healthier and more personalized food choices. Unlike traditional approaches that neglect nutritional and lifestyle dimensions, SFRA integrates user profiles enriched with dietary needs, preferences, and geographic data to deliver context-aware recommendations. Our system evaluates and ranks food and restaurant options by considering nutrition, ingredients, and contextual relevance, enabling users to make informed choices that balance taste with health goals. The second system is an innovative multimodal recommendation approach that exploits heterogeneous data sources (user preferences, spatio-temporal context and emotional) and leverages Graph Neural Networks (GNNs) to model complex relationships between users, items, and contextual factors. Furthermore, we introduce a multi-list recommendation mechanism, designed to provide multiple personalized suggestion lists based on different criteria (relevance, diversity, context), thereby enhancing personalization while reducing user disorientation.

Keywords: Recommender Systems, Multimodal Data, Graph Neural Networks (GNN), Multi-list Recommendation, Multi-criteria Decision Making.

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ABBREVIATIONS

ACF	Autoencoder-based Collaborative Filtering
AE	Autoencoder
AI	Artificial Intelligence
AHP	Analytic Hierarchy Process
ALS	Alternating Least Squares
AM	Attentional Models
AN	Adversarial Networks
ANN	Artificial Neural Network
API	Application Programming Interface
APIs	Application Programming Interfaces
AUC	Area Under the Curve
BERT	Bidirectional Encoder Representations from Transformers
BMI	Body Mass Index
BMR	Basal Metabolic Rate
BPR	Bayesian Personalized Ranking
BPSO	Binary Particle Swarm Optimization
BPTT	Backpropagation Through Time
BFMM	Bayesian Flexible Mixture Model
BFMM-CR	Bayesian Flexible Mixture Model - Context Relevant
CBF	Content-Based Filtering
CBCNN	Context-Based Convolutional Neural Network

CARS	Context-aware Recommender Systems
CatBoost	Categorical Boosting
CA-RNN	Context-Aware Recurrent Neural Networks
CDAE	Collaborative Denoising Auto-Encoder
CF	Collaborative Filtering
CFRS	Collaborative Filtering Recommender Systems
CI	Consistency Index
CMFP	Collaborative Mining and Filtering Process
CNN	Convolutional Neural Network
COPRAS	Complex Proportional Assessment of Alternatives
CRM	Customer Relationship Management
CR	Consistency Ratio
CS	Cosine Similarity
CSLIM	Contextual Sparse Linear Method
CTR	Click-through Rate
DBSCAN	Density-Based Spatial Clustering of Applications with Noise
DCG	Discounted Cumulative Gain
DDTRS	Disease Diagnosis and Treatment Recommendation System
DIETOS	DIET-Organizer System
DL	Deep Learning
DLRS	Deep Learning-based Recommender Systems
DNN	Deep Neural Networks
DRL	Deep Reinforcement Learning
DQN	Deep Q-Network
ELECTRE	Elimination and Choice Translating Reality
ELM	Extreme Learning Machine
EnsTM	Ensemble Topic Modelling
ERS	Educational Recommender Systems
FNDDS	Food and Nutrient Database for Dietary Studies
FGCN	Feature-aware Graph Convolutional Network
GANs	Generative Adversarial Networks
GBDT	Gradient Boosting Decision Trees

GRU	Gated Recurrent Units
HealthRecSys	Health Recommendation System
HIFCF	Hybrid Intelligent Fuzzy Collaborative Filtering
HPMF	Hybrid Probabilistic Matrix Factorization
HR	Hit Rate
HRS	Health Recommendation System
ICA	Independent Component Analysis
IDE	Integrated Development Environment
IP	Internet Protocol
IPSO	Improved Particle Swarm Optimization
IoT	Internet of Things
KNN	k-Nearest Neighbor
LBSNs	Location-Based Social Networks
LDA	Latent Dirichlet Allocation
LDOS-CoMoDa	Linked Open Data Semantic - Context-aware Movie Dataset
LightGBM	Light Gradient Boosting Machine
LR	Logistic Regression
LRRFA	Localization Restaurant Recommendation Filtering Algorithm
LSTM	Long Short-Term Memory
LSTPM	Long- and Short-Term Preference Modeling
MAE	Mean Absolute Error
MAP	Mean Average Precision
MAU	Multi-Attribute Utility
MCDA	Multi-Criteria Decision Analysis
MCDM	Multi-Criteria Decision-Making
MDPs	Markov Decision Processes
MF	Matrix Factorization
ML	Machine Learning
MLP	Multilayer Perceptron
MMSE	Multi-Model Stacking Ensemble
MUAT	Multi-Attribute Utility Theory

NADE	Neural Autoregressive Distribution Estimation
NaN	Not a Number
NARM	Neural Attentive Recommendation Machine
NB	Naive Bayes
NDCG	Normalized Discounted Cumulative Gain
NDPM	Normalized Distance-based Performance Measure
NeuMF	Neural Matrix Factorization
NFM	Neural Factorization Machines
NIS	Negative Ideal Solution
NLP	Natural Language Processing
NMF	Non-negative Matrix Factorization
NRMF	Network Regularized Matrix Factorization
PCA	Principal Component Analysis
PCC	Pearson Correlation Coefficient
PAE	Product Attribute Extraction
PCRS	Personalized Course Recommendation System
PIS	Positive Ideal Solution
POI	Points of Interest
PROMETHEE	Preference Ranking Organization Method for Enrichment Evaluations
PTIS	Personalized Tourism Information Service
QoS	Quality of Service
RBFNs	Radial Basis Function Neural Networks
RBM	Restricted Boltzmann Machine
RBMs	Restricted Boltzmann Machines
RBP	Rank-biased Precision
RCNN	Region-based Convolutional Neural Network
RF	Random Forest
RFID	Radio Frequency Identification
RL	Reinforcement Learning
RMSE	Root Mean Squared Error
RNN	Recurrent Neural Network
RSIoT	Recommender System for Internet of Things

RSs	Recommendation Systems
SDAE	Stacked Denoising Autoencoder
SDAEs	Stacked Denoising Autoencoders
SFRA	Smart Food and Restaurant Advisor
SLIM	Sparse Linear Method
SNRS	Social Network-based Recommender System
SOMs	Self-Organizing Maps
SPM	Sequential Pattern Mining
SRSs	Sequential Recommendation Systems
SVD	Singular Value Decomposition
SVD++	Singular Value Decomposition with implicit feedback
SVM	Support Vector Machine
C-SVM	Context-aware Support Vector Machine
C-SVM-CF	Context-aware SVM using Collaborative Filtering
TADSAM	Time-aware Dynamic Self-Attention Model
TD	Decision Tree
TDEE	Total Daily Energy Expenditure
TDLGC	Time-aware Deep Learning with Graph Clustering
TF-IDF	Term Frequency-Inverse Document Frequency
THOR	Hybrid Offer Ranker
TiSASRec	Time-interval aware Self-Attention Sequential Recommendation
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
UDL	University Digital Libraries
ULP	User Learning Path
UPR	Universal Profiling and Recommendation
USA	United States of America
UtA	Utility Additive
VCs	Virtual Communities
WW	Worldwide
XGBoost	eXtreme Gradient Boosting

INTRODUCTION

General context and issues

The significant increase in information on the Internet has made it challenging for individuals to choose services or products that meet their needs. To address this issue, modern research focuses on developing tools for personal recommendations to simplify decision-making and discovery. These tools offer customized recommendations, presenting users with choices they may not have discovered on their own. Consequently, online recommendation systems have become crucial in shaping opinions and decisions across various fields, due to their ability to deliver personalized information effectively [9]. Recommendation systems are sophisticated tools designed to offer users suggestions by predicting their preferences. By analyzing user data, these systems help manage the vast amount of information users encounter daily, assisting them in choosing what meets their needs and preferences. Personalized recommendations enhance the user experience across various domains, such as products, movies, music, articles, or social media content [161]. By employing data extraction and analysis methods, these systems identify user preferences using advanced algorithms, providing tailored recommendations that enhance user satisfaction and improve the overall experience. The effectiveness of recommendation systems in discovering user preferences has made them crucial across various sectors. These systems are widely used to enhance user interaction and maintain satisfaction. In e-commerce, platforms like Amazon and eBay rely heavily on recommendation systems to suggest customized products. Similarly, Netflix and Spotify use these systems to recommend movies and music [287], increasing user engagement by providing content that matches their preferences.

On the other hand, social media platforms like Facebook, Twitter, and Instagram use recommender systems to increase user interaction by suggesting posts and advertisements that align with users' preferences and interests. Similarly, professional networks such as LinkedIn recommend posts from similar users to help expand their networks and professional circles. In the realm of news and content aggregation, sites like Google News and Medium offer personalized articles and discussions, ensuring that users find content that matches their preferences [182]. Recommendation systems have revolutionized online advertising by tailoring ads to users' preferences and behaviors, significantly enhancing the effectiveness of advertising campaigns. In the education sector, platforms such as Coursera and Udemy employ these systems to suggest courses and learning paths customized to individual learners [141]. Travel platforms such as

TripAdvisor and Airbnb suggest destinations and activities based on user preferences [1] . In healthcare, recommendation systems provide personalized health advice and treatment plans, enhancing patient care and outcomes [291].

Recommender systems face several challenges that limit their effectiveness. A major issue is the lack of relevant data, which leads to inaccurate recommendations, particularly for new users (cold-start problem) and in cases of data sparsity. Additionally, user disorientation and information overload can make decision-making difficult, as excessive or poorly structured suggestions may cause confusion and choice fatigue. Traditional systems also lack contextual awareness, often ignoring crucial factors like time, location, weather, and emotional states, which can impact user preferences. Moreover, many recommendation models rely on single-criterion filtering, failing to incorporate multi-criteria decision-making (MCDM) approaches that consider diverse factors such as price, quality, and social influence. Lastly, digital traces from social media remain underutilized, despite offering valuable insights into user behavior.

Objectives

The main objectives of this thesis are threefold:

- To enhance recommendation accuracy by integrating machine learning and deep learning methods with multi-criteria decision-making (MCDM) approaches. This combination enables the system to consider diverse factors (such as price, quality, brand, and social influence) while generating more relevant and personalized recommendations.

- To design multimodal recommender systems capable of exploiting heterogeneous data, including user preferences, contextual information, emotional states, and social interactions. By leveraging these multimodal inputs and employing Graph Neural Networks (GNNs) for relational modeling, the system can generate adaptive and context-aware recommendations.

- To introduce a multi-list recommendation mechanism, providing users with multiple suggestion lists tailored to different criteria (e.g., relevance, diversity, and context). This innovation aims to reduce user disorientation, enhance personalization, and improve decision-making in various application domains.

Scientific Contributions

The main scientific contributions of this thesis can be summarized as follows:

- ✍ **First contribution**: We propose the Smart Food and Restaurant Advisor (SFRA), a multi-criteria recommender system that integrates deep learning models with MCDM techniques. SFRA focuses on health-conscious food choices by incorporating user preferences, dietary needs, and geographic context. The system demonstrates how combining machine learning with multi-criteria analysis can enhance personalization and support healthier decision-making.

✍ **Second contribution**: We develop a Multi-list Recommender System for Smart Tourism, which integrates multimodal data (social media interactions, contextual information, and emotional states) with deep learning and GNNs. By analyzing user behavior and modeling relationships between tourists, destinations, and contexts, the system generates multiple recommendation lists that improve diversity, adaptability, and overall user satisfaction.

Together, these contributions advance the state of the art in recommender systems by demonstrating how multimodal data integration, GNN-based relational modeling, and multi-list recommendations can improve personalization, reduce disorientation, and provide more effective decision support across different domains.

Thesis Roadmap

This thesis is structured into two main parts. The first part provides a comprehensive review of recommender systems, covering fundamental concepts, techniques, and advanced methodologies, including machine learning, deep learning, and multi-criteria decision-making approaches. The second part focuses on proposed recommendation systems for specific domains, including food and restaurant recommendations and smart tourism.

❖ **Part I: Backgrounds, Preliminaries, Basic Concepts and Literature Review**

❏ *Chapter 01: "Introduction to recommender systems"*
This chapter provides a comprehensive overview of recommender systems, covering their definition, historical development, and core techniques such as content-based, collaborative, hybrid, and context-aware filtering. It explores key challenges, including data sparsity, cold start problems, algorithmic scalability, and ethical concerns like bias and fairness. Various evaluation metrics for assessing recommendation performance are discussed, alongside their relevance in different application domains. The chapter also highlights the state-of-the-art applications of recommender systems across industries such as e-commerce, healthcare, education, and entertainment.

❏ *Chapter 02: "Machine / Deep Learning, and Multi-Criteria Decision-Making (MCDM) approaches for recommendation"*
This chapter examines recommendation system approaches using Machine Learning, Deep Learning, and Multi-Criteria Decision-Making (MCDM) techniques. It covers collaborative and content-based filtering, hybrid models. Deep Learning approaches, including autoencoders, CNNs, RNNs, and Transformers, are explored for advanced recommendations. The chapter also highlights MCDM methods like AHP, TOPSIS, and PROMETHEE, showing their integration with Machine Learning to enhance recommendation accuracy. A comparative analysis discusses the strengths and limitations of these approaches, concluding with insights into their applications in modern recommendation systems.

❖ **Part II: Proposed Recommender Systems**

❏ *Chapter 03: "A Multi-Criteria Food and Restaurant Recommendation System"*

This chapter introduces the research questions and provides a description of the datasets used. Next, we present the proposed architecture of the SFRA system. Finally, we detail the experimental evaluation, followed by the presentation and discussion of the results.

❏ *Chapter 04: "A Graph-Aware Multimodal Deep Learning Multi-List Recommender System for Smart Tourism"*

This chapter introduces our research questions, followed by a detailed description of the proposed approach. Next, we present the datasets used, the experiments conducted, and an analysis of the obtained results.

Part I

Backgrounds, Preliminaries, Basic Concepts and Literature Review

CHAPTER 1

INTRODUCTION TO RECOMMENDER SYSTEMS

Chapter contents

1.1   Introduction

In today's digital world, recommendation systems (RSs) are essential, offering immense value and convenience to users across various domains. Their significance cannot be overstated, as they enhance the intelligence and efficiency of platforms and services. The effectiveness of a recommendation system (RS) depends on the accuracy and efficiency of its techniques, ensuring relevant and useful suggestions for individual users [9]. Modern research focuses on personalized recommendation systems that simplify decision-making and enhance user experiences. These systems analyze user data to predict preferences and provide tailored suggestions across various fields, including e-commerce, entertainment, social media, education, and healthcare. Platforms such as Amazon, Netflix, and LinkedIn utilize recommendation systems to improve user engagement and satisfaction [161]. Their growing adoption underscores their importance in enhancing digital interactions and optimizing user experiences.

This chapter explores the key concepts and definitions related to recommender systems, along with their various techniques. Section 1.2 presents the definition and history of recommender systems. Section 1.3 discusses the techniques used in recommendation systems. The challenges and limitations associated with these systems are examined in Section 1.4. Section 1.5 discusses evaluation metrics used to assess recommendation performance. Finally, Section 1.6 reviews related works, focusing on their applications across different fields.

1.2   Definition and History of Recommender Systems (RS)

In this section, we will present: (1) RSs different definitions in section 1.2.1 and (2) the history of RS in section 1.2.2.

1.2.1 Recommender System definition

Recommender systems can be defined in several ways, given the diversity of classifications proposed for these systems, but there is a general definition from Robin Burke [39] which defines them as follows:

> "Systems capable of providing personalized recommendations to guide the user to interesting and useful resources within a large data space.".

The two basic entities that appear in all recommendation systems are the user and the item. The "user" is the person who uses a recommendation system, gives opinions on various items, and receives new recommendations from the system. The "item" is the term generally used to designate what the system recommends to users.

The input data for a recommender system depends on the technique of filtering algorithm employed. Generally, they fall into one of the following categories:

- **Estimates:** These are also referred to as ratings or votes, representing users' opinions on items. For example, a scale of 1 to 5 might be used, where 1 indicates "I don't like it" and 5 signifies "I like it".

- **Demographics:** This refers to information such as users' age, gender, country, and education. This type of data is generally difficult to obtain and is normally collected explicitly.

- **Content data:** This is based on a textual analysis of documents linked to the elements evaluated by the user. The characteristics extracted from this analysis are used as inputs in the filtering algorithm to deduce a user profile [224].

The concept of recommender systems has several definitions that differs from a research to another based on its application field.

- Resnick and Varian [246] define recommender system as: *"a means of assisting and augmenting the social process of using recommendations of others to make choices when there is no sufficient personal knowledge or experience of the alternatives."*.

- In 2002, authors in [243] considered the recommender systems as: *"Systems help people make decisions in these complex information spaces. Recommenders suggest to the user items that she may value based on knowledge about her and the space of possible items. A news service, for example, might remember the articles a user has read. The next time she visits the site, the system can recommend new articles to her based on the ones she has read before."*.

- In another research, Prem and Vikas [234] define recommender system as: *"Systems that have evolved to fulfill the natural dual need of buyers and sellers by automating the generation of recommendations based on data analysis."*.

- In 2011, Robin and his colleagues [248] consider recommender system as: *"The tools for interacting with large and complex information spaces. They provide a personalized view of such spaces, prioritizing items likely to be of interest to the user."*.

- In 2020, Altulyan and his colleagues [17] gives a new definition of RS where they consider it as: *"A system that proactively recommends items that users may prefer. It has evolved through three main generations from RS for E-commerce, context-and social-aware RSs, and RSs that seek to handle IoT data.".*

The recommendation system's primary goal is to filter relevant information for users by filtering through a large volume of data. It extracts user preferences from historical interactions, then employs machine learning algorithms to generate a ranked list of recommended items tailored to the user's interests.

The recommendation system architecture illustrated in Figure 1.1 :
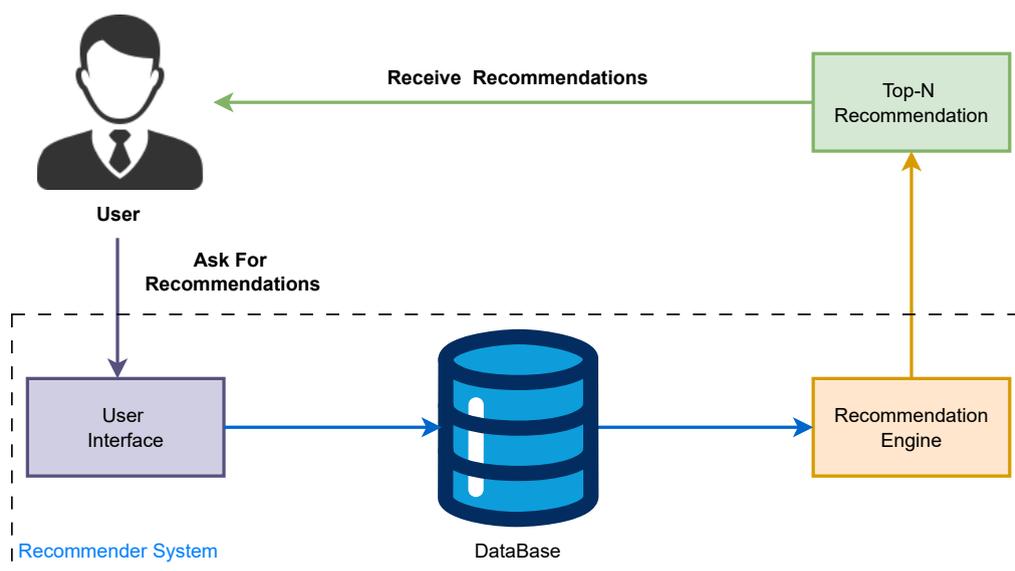
FIGURE 1.1: Recommendation System Architecture [176].

1.2.2 History of recommendation systems

Recommender systems (RSs) have rapidly advanced in recent years and gained widespread popularity across various fields, including e-commerce, streaming services, social media, news aggregation, online advertising, education, travel, and healthcare. Studies highlight their role in improving user experiences[63]. RSs help address the issue of information overload, especially in online environments, by suggesting relevant items to users, such as articles, books, movies, and restaurants, based on their preferences.

In 1979, the first recommendation system [184] was proposed. At that time, the most common method to address the problem of information sharing in an email environment was to distribute lists based on interest groups. Recommendation systems have become integral to many applications and websites, offering tailored suggestions for services and items. The first known use of a recommendation system was in 1979 with Grundy [247], which suggested books based on user preferences.

In the 1990, Tapestry [86] emerged as the first recommendation system applied in the commercial sector. A few years later, many academic recommendation systems appeared in 1994 and 1995, such as the movie reporting and recommendation system designed to help users find their favorite articles named "GroupLens recommender system" [245] by a research lab at the University of Minnesota, USA and the music recommendation "Ringo" proposed by Maes and Shardanand [275], BellCore, and Jester.

Another major advancement in the late 1990 was Amazon's collaborative filtering, one of the most widely known recommendation techniques. Since then, collaborative filtering-based systems have become increasingly popular and have been adopted by many e-Commerce platforms, leading to the development of numerous recommendation tools. Amazon's success also inspired the creation of hybrid recommendation algorithms that combine multiple methods [166].

After the successful rise of recommendation systems in the late 1990s, the industry began to invest heavily in RS research. A prominent example is the Netflix Prize, launched in 2006 by Netflix, which awarded 1 million US Dollars to the team that developed the best movie recommendation system. The winning team was announced in 2009. In 2010, YouTube also implemented a recommendation system on its platform [61], With the rise of the Internet and web applications, they have become increasingly popular across various domains.

For all recommendation systems developed to date, the collection of user and/or item data represents a key step in the personalization process. A deep understanding of different recommendation techmiques helps enhance system performance. Efficient and accurate recommendation techniques are essential for providing personalized and valuable suggestions to users. The following section 1.3 details the techniques of recommender system can use and the issues involved in collecting it.

1.3 Techniques of Recommendation Systems

There are several classifications of recommendation techniques as illustrated in Figure 1.2 has evolved over the years, beginning with foundational work in the early 1990s and expanding as the field developed :

Classification by Patti Maes (1994)

Patti Maes introduced the concept of *collaborative filtering*, which became one of the earliest and most influential classifications in recommender systems. Collaborative filtering involves predicting a user's preferences by analyzing the preferences of other users with similar tastes. This method laid the groundwork for many of the systems in use today.

Classification by Paul Resnick and Hal R. Varian (1997)

Building on the concept of collaborative filtering, Resnick and Varian provided a formal classification of recommender systems. They identified three broad categories [246]:

- **Content-Based Filtering:** Recommendations recommends items by analyzing the content of items that a user has previously interacted with, suggesting similar content.
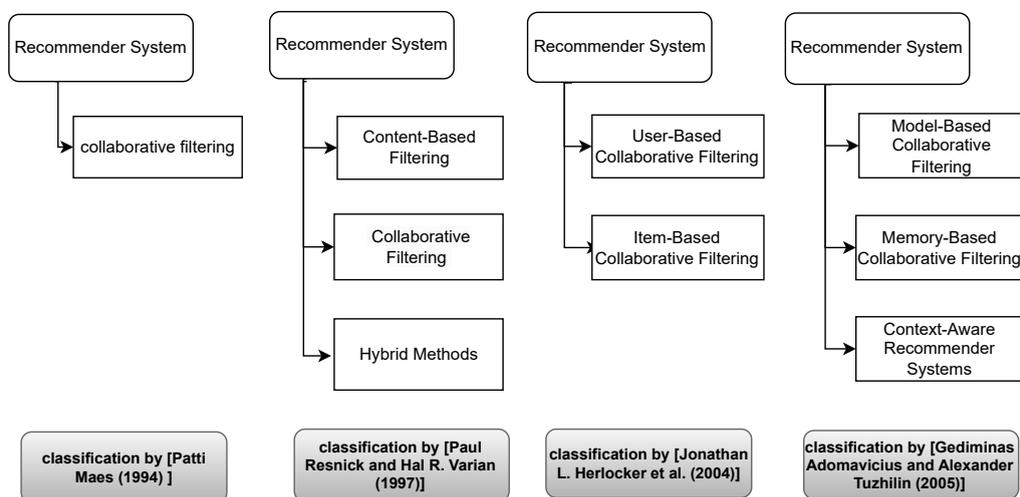
FIGURE 1.2: Recommendation Techniques.

- **Collaborative Filtering:** Recommendations are based on the preferences of users who share similar tastes.

- **Hybrid Approaches:** These technique combine both content-based and collaborative filtering techniques to enhance recommendation accuracy.

Classification by Jonathan L. Herlocker et al. (2004)

Herlocker and colleagues further refined the classification where they propose a new classes: User-based collaborative filtering and Item-based collaborative filtering [106].

Classification by Gediminas Adomavicius and Alexander Tuzhilin (2005)

Adomavicius and Tuzhilin [72]expanded the classification of recommender systems by introducing more granular distinctions within collaborative filtering [5]:

- **Model-Based Collaborative Filtering:** Uses machine learning models to predict user preferences based on past interactions.

- **Memory-Based Collaborative Filtering:** Relies on the memory of past user-item interactions, using techniques like nearest neighbors to make recommendations.

- **Context-Aware Recommender Systems:** These systems take into account additional contextual information (e.g., time, location) to provide more personalized recommendations.

In recent researches, the most classification used is: content-based, collaborative, context-aware, and hybrid filtering.

1.3.1 Content-Based Filtering (CBF)

Content-based filtering recommends items by analyzing the characteristics of those a user has previously liked or interacted with. It builds a personalized profile based on item attributes such as categories, or specific features. The system then suggests similar items by identifying patterns in the user's preferences as shown in Figure 1.3. By continuously refining the profile through feedback, it ensures increasingly accurate and personalized recommendations. Essentially, it functions as a tailored information retrieval system, adapting to user interests over time[125].
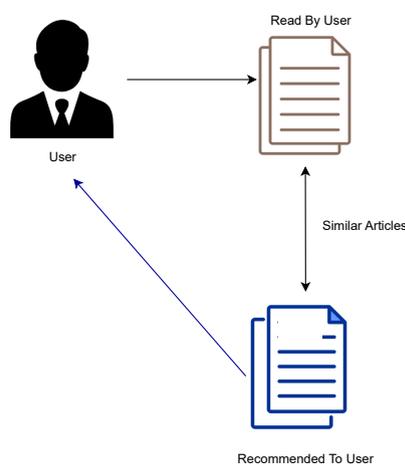
FIGURE 1.3: Content-based filtering technique [276].

1.3.1.1 Mechanism Behind Content-Based Filtering

Content-based filtering focuses on item attributes to match recommendations with a user's preferences. It builds a user profile from past interactions and compares it with item features to generate personalized suggestions [84].

1. **User Profile**: A user profile captures preferences based on past interactions, ratings, and features. To ensure relevant recommendations, the system must adapt to evolving preferences by updating the profile dynamically. As users engage with new content, seamless updates help refine suggestions for greater accuracy over time.

2. **Item Features**: Item features help describe an item and match it with user preferences. Text-based characteristics sush as (title, description, genre), numerical characteristics like (price, rating, popularity), visual and aural elements, and contextual elements sush as (time and place) are some examples.

3. **Recommendation Engine**: The content-based recommendation engine matches user preferences with item features to generate personalized suggestions. By analyzing item characteristics, it identifies those that align with individual tastes. The goal is to provide each user with a tailored list of relevant recommendations.

1.3.2 Collaborative Filtering (CF)

Collaborative filtering is a foundational approach in recommendation systems, designed to make personalized suggestions by identifying users with similar preferences. Instead of relying on the specific features of items like in content-based recommendation, it identifies patterns in user behavior to recommend items based on shared preferences among users. By leveraging the collective experiences and tastes of a large user base, this method enhances the accuracy and relevance of recommendations, making it effective in diverse applications [201]. Figure 1.4 illustrated how collaboratif filtering technique recommendation works :
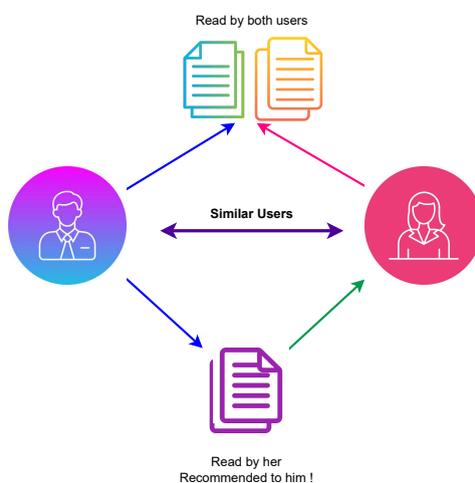
FIGURE 1.4: Collaborative filtering technique [239].

1.3.2.1 Collaborative Filtering Mechanism

Collaborative filtering relies on three key components: the user profile, community data, and the recommendation engine. Community data aggregates user preferences, behaviors, and interactions to identify patterns. The recommendation engine uses this data along with the user's profile to generate personalized suggestions. Together, these elements ensure tailored and relevant recommendations for each user.

1. **User Profile**: The user profile is essential in collaborative filtering, capturing ratings and interactions that define user preferences. These ratings, collected through explicit (reviews, ratings) or implicit (clicks, browsing history) feedback, form the basis of a rating table. This data is organized into a rating table 1.1, which serves as the foundation for predicting preferences and making personalized recommendations.

2. **Community Data**: Community data, consisting of user ratings and reviews, identifies patterns and groups users with similar interests. By analyzing this data, the system suggests items to users based on the preferences of like-minded individuals, forming the core of collaborative filtering.

TABLE 1.1: Table rating in collaborative filtering

User	Item 1	Item 2	Item 3	Item 4	Item 5
User 1			7	6	7
User 2			5	6	7
User 3			6	6	7
User 4	7	5			7
User 5	7	6			7

3. **Recommendation Engine**: Using community data and user profiles, collaborative filtering identifies patterns to match users with similar preferences. Various methods analyze these correlations to generate personalized recommendations. This ensures each user receives a tailored list of suggested items.

1.3.3 Hybrid Filtering (HF)

Hybrid filtering combines collaborative and content-based techniques to improve recommendation accuracy as shown in Figure 1.5. It integrates user profiles, community data, product features, and a recommendation engine, leveraging the strengths of both approaches. Hybrid systems overcome individual limitations and enhance personalization [201].
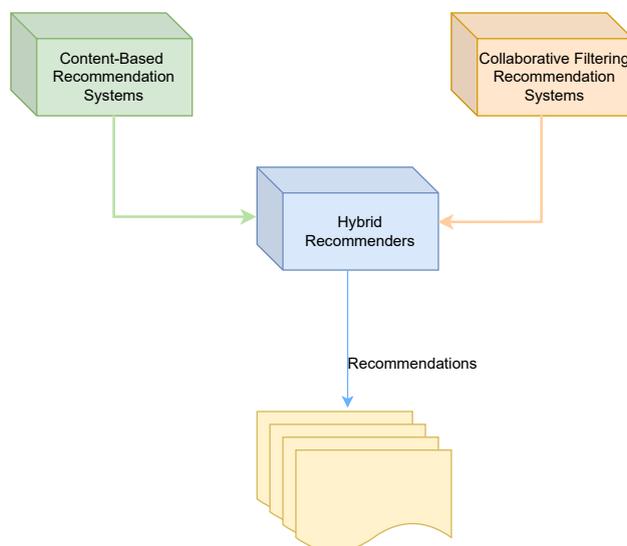
FIGURE 1.5: Hybrid filtering technique [177].

Various methods exist for hybridization, but there is no consensus within the research community on a single best approach, as each method offers different strengths and trade-offs depending. Burke [40] identified seven distinct methods for hybridization:

1. **Weighted:** The scores or predictions from each technique are combined into a single, aggregated result.

2. **Switching:** The system alternates between different recommendation techniques based on the context or situation.

3. **Mixed:** The recommendation lists generated by both techniques are merged into a unified list.

4. **Feature Combination:** Data from both techniques are combined and fed into a single recommendation algorithm for joint processing.

5. **Feature Augmentation:** The output of one technique is used as input for the other, enhancing its performance.

6. **Cascade:** One technique generates an initial ranking of items, and a second technique refines this list to produce the final recommendations.

7. **Meta-level:** Similar to feature augmentation, but instead of using the result list, the learned model from one technique is used as input for the second technique.

1.3.3.1 Hybrid Filtering Mechanism

The hybrid filtering mechanism combines content-based and collaborative filtering to improve recommendation quality. While content-based methods rely on item attributes, collaborative filtering analyzes user rating patterns. Integrating these approaches enhances accuracy. Hybridization generally occurs in two phases:

1. **Generate Recommendations:** Collaborative filtering and other techniques are applied independently to produce a set of initial candidate recommendations.

2. **Combine Recommendation Sets:** These preliminary recommendation sets are merged using methods to create the final set of recommendations. This process balances the strengths of each technique to enhance accuracy and personalization for users.

1.3.4 Context-Aware Recommendation Systems (CARS)

Classical recommendation systems focus only on user and item factors, ignoring contextual influences like time, mood, and environment. Context-Aware Recommendation Systems (CARS) enhance recommendations by integrating these factors, making them more dynamic and personalized. Unlike traditional models, CARS actively adapt to users' moods, behaviors, and locations to refine suggestions. With the rise of mobile devices, these systems aim to deliver timely, relevant suggestions tailored to the user's current situation. The main challenge is offering flexible, dynamic recommendations that adapt to factors like time constraints and proximity. Adomavicius et al. [6] emphasized the importance of incorporating contextual information into recommendation systems by extending the traditional two-dimensional model (user and item) into a three-dimensional model (user, item and context => rating).

Hong et al. [113] describe several forms of user context that enhance recommendation systems:

1. **Activity:** Users activities range from low level actions like eating or reading to high level behaviors such as domestic or professional tasks. Outdoor activities, tracked by smartphones, also inform recommendations based on physical movements (such as using accelerometer data to recognize daily activities).

2. **Emotion:** Emotional context, integral to understanding user needs, can be derived from facial expressions, physiological signs (e.g., heart rate), or social media interactions, offering insights into the user's emotional state.

3. **Multi-Dimensional Information:** By combining various contextual factors, such as climate and mood, systems can refine recommendations. However, evaluating the relevance and weight of each factor is essential to avoid overwhelming the recommendation process.

4. **Additional Contextual Factors:** Context includes time (e.g., time of day), location (e.g., home, work), weather conditions, device type, and the user's current state (e.g., emotional state, activity).

1.3.4.1 Mechanism of Context-Aware Recommender Systems

Context-Aware Recommender Systems (CARS) enhance traditional recommendation models by incorporating contextual factors such as time, location, mood, and weather. The mechanism of CARS involves the following key steps:

1. **Context Acquisition**: Collecting contextual data from various sources, including mobile sensors, social media, user interactions, and external APIs (e.g., weather or geolocation services).

2. **Context Representation**: Structuring contextual data into relevant dimensions (e.g., temporal, spatial, social, emotional) to integrate with user-item interactions.

3. **Context Modeling**: Incorporating context into the recommendation process using one of three methods:

   - **Pre-filtering**: Filtering data before training the recommendation model to consider only relevant interactions.
   - **Post-filtering**: Generating recommendations first, then adjusting them based on contextual relevance.
   - **Contextual Modeling**: Directly embedding context as a feature in the recommendation algorithm.

4. **Recommendation Generation**: Applying machine learning techniques (e.g., collaborative filtering, deep learning, or hybrid models) to generate personalized suggestions based on contextual and historical data.

5. **Evaluation & Adaptation**: Continuously refining recommendations through user feedback and real-time updates to ensure relevance and accuracy in dynamic environments.

1.4 Challenges and issues in recommendation systems

The issues and difficulties in recommendation systems are covered in this section, along with the several approaches that researchers have taken to overcome these issues. Recommendation engines might be a blessing for the modern world, but if users can readily manipulate them, they can also be a nightmare. Thus, recommendation systems have become an essential tool in various domains, but they face several challenges that can hinder their effectiveness. Below, we categorize and discuss these challenges.

1.4.1 Data Challenges

1.4.1.1 Cold Start Problem

The cold start problem is a major challenge in recommendation systems, particularly for collaborative filtering (CF), which relies on user-item interactions. It occurs in two forms: user cold start, where new users lack interaction history, and item cold start, where new items have insufficient feedback. Overcoming this requires innovative approaches to deliver meaningful recommendations despite limited data.

Addressing these challenges cold start problem, hybrid recommendation systems combine content-based filtering and collaborative filtering. Content-based methods use item features, while collaborative filtering leverages user behaviors and preferences to make predictions. By merging these approaches, hybrid systems deliver relevant recommendations even with limited historical data, enhancing personalization, user satisfaction, and overall system performance [219, 352].

1.4.1.2 Sparsity

Data sparsity is a common challenge in large-scale data analysis, especially in recommender systems, where only a small fraction of items are rated by users. This reduces recommendation accuracy significantly. Techniques like Singular Value Decomposition (SVD), model-based collaborative filtering, and demographic filtering help address this by identifying latent patterns, leveraging statistical models, and using user demographic data. The vast number of products and user reluctance to provide ratings exacerbate the issue, leading to inefficiency in computational learning. Dimensionality reduction methods can alleviate sparsity by reducing irrelevant items, enhancing computational efficiency.

1.4.1.3 Privacy

Recommender systems provide stronger services by utilizing personal information, but this raises concerns about data security and privacy. Users may be reluctant to share their data due to privacy issues, especially in collaborative filtering (CF) systems [290], which store sensitive information in centralized databases prone to hacking and misuse. To address this, cryptographic techniques can ensure personalized recommendations without exposing user data [230]. Additional methods like randomized perturbation and Semantic Web technologies, including ontologies and natural language processing, can protect user privacy while enabling effective recommendations [107].

1.4.1.4 Imbalanced

Imbalanced data is a common issue in RSs, where popular items often dominate, leading to biased suggestions. This bias occurs as frequently interacted items overshadow less popular ones, reducing diversity and limiting personalized recommendations. To address this, methods like re-sampling, cost-sensitive learning, or domain-specific constraints can balance the data, while techniques such as embedding-based methods and debiasing algorithms help mitigate the influence of popular items. Addressing data imbalance improves fairness and ensures more inclusive, personalized recommendations [48].

1.4.1.5 Noisy

Noisy data, stemming from errors, inconsistencies, or irrelevant information in user interactions, significantly impacts recommendation system quality. Users may provide inaccurate feedback, unintentionally engage with products, or act in ways that don't reflect true preferences. To address this, preprocessing techniques like data cleansing, anomaly detection, and outlier removal are applied, while advanced methods like noise-resilient neural networks and robust matrix factorization help minimize noise's impact [9]. Effectively managing noisy data enhances recommendation accuracy, improving user satisfaction and system reliability [328].

1.4.2 Algorithmic Challenges

1.4.2.1 Scalability

Scalability challenges in recommender systems arise as collaborative filtering methods require extensive training data, leading to increased computational demands with growing users and products [121, 251]. To address this, companies like Amazon combine subject diversification algorithms with collaborative filtering for efficient recommendations. Strategies like dimensionality reduction and clustering improve computational efficiency by simplifying data structures and grouping users into manageable clusters [175]. These methods ensure scalable, high-quality recommendations even as data volume expands [265, 266].

1.4.2.2 Interoperability

Interoperability in IoT-Based Recommender Systems is a significant challenge, as IoT devices often operate on diverse standards and protocols. Seamless communication between constrained and unconstrained entities requires adaptable networking protocols that bridge these differences. To overcome interoperability barriers, the system should incorporate standardized frameworks, middleware solutions, and protocol translation mechanisms. This ensures smooth data exchange, enhances system efficiency, and enables more accurate and context-aware recommendations in heterogeneous IoT environments [267].

1.4.2.3 Overfitting

Overfitting in recommendation systems occurs when a model becomes too tailored to the training data, capturing noise instead of general patterns, and failing to generalize to new users or items

[290]. This results in overly specific recommendations that may not be relevant in real-world scenarios. Regularization techniques, data augmentation, and hybrid recommendation models are commonly used to mitigate overfitting and improve generalization performance [354].

1.4.2.4 Bias

bias in RS can be categorized into selection, conformity, exposure, and position biases. Moreover, learning-based models may not generalize well in real-world scenarios due to discrepancies between training and test distributions. External factors, such as exposure mechanisms and public opinion, further distort user preferences, impacting recommendation quality and fairness [48].

1.4.3 User-Centric Challenges

1.4.3.1 Diverse Preferences

Users have diverse, evolving, and multifaceted preferences influenced by various factors such as mood, context, and social trends [6]. Capturing these dynamic preferences is a significant challenge in recommendation systems, as traditional models often assume static user interests. Advanced approaches, including context-aware recommendation systems and deep learning-based models, have been proposed to adapt to these changes and provide more personalized recommendations.

1.4.3.2 Serendipity

Serendipity in recommendation systems refers to the balance between relevance and surprise suggesting items that are not only relevant but also novel and unexpected to the user. A serendipitous recommendation introduces users to content they might not have actively searched for but are likely to enjoy, thus enhancing engagement and discovery. Techniques such as diversity enhanced collaborative filtering and reinforcement learning have been explored to improve serendipitous recommendations.

1.4.3.3 Trust

Trust in Recommender Systems is a critical challenge, especially when dealing with large-scale distributed sensor networks. The system must be resilient against malicious nodes by implementing robust mechanisms to identify and mitigate untrustworthy entities. One effective approach is to establish a trust and reputation framework, where each IoT device continuously evaluates the reliability of others. By integrating trust assessment techniques, the system can enhance security, reduce the impact of fraudulent activities, and ensure more reliable recommendations in dynamic IoT environments [297].

1.4.3.4 Engagement

User engagement refers to the continuous interaction of users with a recommendation system over time. Maintaining long-term engagement is crucial for ensuring user satisfaction and retention. However, repetitive or irrelevant recommendations can lead to user fatigue, reducing engagement. Strategies to enhance engagement include diversity-aware recommendations, novelty driven suggestions, and reinforcement learning techniques that adapt to evolving user preferences.

1.4.4 Contextual Challenges (Dynamic Environments)

Dynamicity involves managing three key aspects: real-time discovery of IoT devices at the network level [345], adaptive identification of user preferences based on contextual changes [189], and the ability to deliver on demand, real-time recommendations [259, 260]. Additionally, factors such as device locations, environmental conditions, and resource availability are continuously evolving [18]. To ensure efficiency, RSIoT must employ dynamic adaptation techniques, context-aware modeling, and real-time data processing to provide accurate and responsive recommendations in ever-changing IoT environments.

1.4.5 Ethical Challenges

1.4.5.1 Filter Bubbles

A filter bubble occurs when recommendation algorithms reinforce user biases by continuously suggesting content similar to what a user has previously engaged with. This limits exposure to diverse perspectives and can create an echo chamber effect, where users only encounter information that aligns with their existing beliefs. Such reinforcement can have societal implications, influencing public opinion and reducing open-mindedness in discussions on various topics, including politics, news, and culture [207].

1.4.5.2 Manipulation

Recommendation systems can be exploited to spread misinformation, manipulate public perception, or promote undesirable behaviors. This occurs when algorithms prioritize engagement over content quality, leading to the amplification of sensationalist or misleading information [13]. Additionally, adversarial attacks on recommendation models can deliberately alter rankings to promote specific products, ideologies, or false narratives [364]. Addressing this challenge requires incorporating trustworthiness and credibility assessments into recommendation algorithms.

1.4.5.3 Fairness

Ensuring fairness in recommendation systems involves mitigating biases that may lead to discrimination based on gender, age, ethnicity, or other demographic attributes [195]. Biases in training data or algorithmic decision-making can result in unequal access to opportunities, such as job recommendations favoring one demographic over another [31]. To enhance fairness, fairness-aware recommendation models have been proposed, integrating techniques such as re-ranking,

adversarial training, and diversity constraints to prevent systematic discrimination [75].

Addressing these challenges requires a combination of advanced algorithms, ethical considerations, and user-centric strategies to improve the performance and trustworthiness of recommendation systems. However, RS's problems and obstacles can be resolved in a number of ways. Utilizing a user's IP address can help alleviate the cold start issue. Location, time, and other contextual details can be obtained from a user's IP address. If products have been bought by people in similar places at similar times, it is feasible to suggest them based on these parameters. In addition, the RS dataset needs to have the most recent and popular things in order for users to see them. On the contrary, when users were being recommended, old items had to be eliminated. It is also possible to employ deep learning techniques to create a recommendation system with greater accuracy. It might remarkably achieve the goal of dimensionality reduction in the large dataset. It aids in the extraction of the dataset's latent properties, potentially producing better suggestions than previously. The sparsity issue arises from the recommendation systems' enormous user and item count. Most of the cells in the users-items matrix contain zeros. However, it has been discovered that clustering can somewhat address this problem. Additionally, the issue of synonyms and abbreviations can be resolved by applying certain natural language processing techniques.

1.5 Evaluation Metrics for Recommendation

A recommender system ranks uncollected items for a target user and suggests the highest-ranked ones. To evaluate its performance, the dataset is typically split into a training set (E_T) and a probe set (E_P), where only the training set is used for recommendations. The choice of evaluation metrics depends on the system's objectives, but ultimately, user satisfaction is the true measure of its success.

1.5.1 Rating Accuracy Metrics

Recommender systems aim to predict users' future interests based on past interactions. Several metrics evaluate their performance, with Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) being widely used. These metrics measure the deviation between predicted and actual ratings. Given $r_{i\alpha}$ as the true rating of object α by user i, $\tilde{r}_{i\alpha}$ as the predicted rating, and E_P as the set of hidden user-object ratings, MAE and RMSE are defined as:

$$MAE = \frac{1}{|E_P|} \sum_{(i,\alpha)\in E_P} |r_{i\alpha} - \tilde{r}_{i\alpha}|, \tag{1.1}$$

$$RMSE = \sqrt{\frac{1}{|E_P|} \sum_{(i,\alpha)\in E_P} (r_{i\alpha} - \tilde{r}_{i\alpha})^2}. \tag{1.2}$$

Lower values of MAE and RMSE indicate better prediction accuracy. RMSE penalizes larger errors more heavily due to squaring the differences. However, these metrics do not consider the ranking of recommendations, making them less effective for evaluating tasks like identifying top-rated items.

1.5.2 Rating and Ranking Correlations

An alternative evaluation approach involves measuring the correlation between predicted and true ratings. Three common correlation measures are:

- **Pearson Correlation Coefficient (PCC)** quantifies the linear relationship between predicted and actual ratings [158]:

$$PCC = \frac{\sum_\alpha (\tilde{r}_\alpha - \bar{\tilde{r}})(r_\alpha - \bar{r})}{\sqrt{\sum_\alpha (\tilde{r}_\alpha - \bar{\tilde{r}})^2}\sqrt{\sum_\alpha (r_\alpha - \bar{r})^2}}. \tag{1.3}$$

- **Spearman Correlation** is computed similarly but ranks are used instead of actual ratings [284].

- **Kendall's Tau** measures ranking agreement [136]:

$$\tau = \frac{C - D}{C + D}, \tag{1.4}$$

  where C is the number of concordant pairs and D is the number of discordant pairs. A variation accounts for ties:

$$\tau \approx \frac{C - D}{\sqrt{(C + D + S_T)(C + D + S_P)}}, \tag{1.5}$$

  where S_T and S_P are the number of tied pairs in true and predicted rankings, respectively.

Another ranking-based metric, Normalized Distance-based Performance Measure (NDPM), compares weakly ordered rankings:

$$NDPM = \frac{2C^- + C^u}{2C}, \tag{1.6}$$

where C^- represents contradictory pairs, C^u compatible pairs, and C the total strict preference relationships in the true ranking.

1.5.3 Classification Accuracy Metrics

For tasks like "Finding Good Objects," where implicit feedback is available, classification-based metrics such as the Area Under the Curve (AUC) are used. AUC measures the probability of correctly ranking relevant items above irrelevant ones:

$$AUC = \frac{n_0 + 0.5n_{00}}{n}, \tag{1.7}$$

where n_0 is the number of cases where relevant items score higher than irrelevant ones, and n_{00} represents ties.

A perfect recommendation list achieves $AUC = 1$, while a random list yields $AUC = 0.5$. Similarly, the Ranking Score (RS) measures the relative ranking of relevant items, with lower scores indicating better performance [100].

Since real users are usually concerned only with the top part of the recommendation list, a more practical approach is to consider the number of a user's relevant objects ranked in the top-L positions. Precision and recall are the most comsmonly used metrics based on this principle.

For a target user i, precision and recall of recommendation, $P_i(L)$ and $R_i(L)$ [362], are defined as:

$$P_i(L) = \frac{d_i(L)}{L}, \quad R_i(L) = \frac{d_i(L)}{D_i},$$
(1.8)

where $d_i(L)$ represents the number of relevant objects (objects collected by user i that are present in the probe set) in the top-L places of the recommendation list, and D_i is the total number of user i's relevant objects.

Averaging precision and recall over all users with at least one relevant object, we obtain the mean precision and recall, $P(L)$ and $R(L)$. These values can be compared with precision and recall resulting from random recommendation, leading to precision and recall enhancements as defined in [362]:

$$\tilde{P}(L) = \frac{P(L)}{\frac{MN}{D}}, \quad \tilde{R}(L) = \frac{R(L)}{\frac{N}{L}},$$
(1.9)

where M and N are the number of users and objects, respectively, and D is the total number of relevant objects.

While precision typically decreases with L, recall always increases with L. To address this, a common metric called the F1-score [223] is used to balance precision and recall:

$$F_1(L) = \frac{2P(L)R(L)}{P(L) + R(L)}.$$
(1.10)

Many other combined precision-recall measurements, such as Average Precision, Precision-at-Depth, R-Precision, and Reciprocal Rank [38], are also used in information retrieval but are less common in recommendation evaluation.

1.5.3.1 Rank-weighted Indexes

Since users have limited patience when inspecting individual objects in the recommendation lists, their satisfaction is best measured by considering the position of each relevant object.

Half-life Utility The half-life utility metric evaluates the utility of a recommendation list to a user by assuming that the likelihood of examining a recommended object decays exponentially with its ranking [36]. The expected utility for user i is given by:

$$HL_i = \sum_{\alpha=1}^{N} \frac{\max(r_{i\alpha} - d, 0)}{2^{(o_{i\alpha}-1)/(h-1)}},$$
(1.11)

where objects are sorted by recommendation score $\tilde{r}_{i\alpha}$ in descending order, $o_{i\alpha}$ represents the predicted ranking of object α in the recommendation list, d is the default rating (e.g., average rating), and the "half-life" h is the rank at which there is a 50% chance the user will examine the object.

Discounted Cumulative Gain (DCG) DCG assigns higher utility to highly ranked relevant objects. For a recommendation list of length L, DCG is defined as [123]:

$$DCG(b) = \sum_{n=1}^{b} r_n + \sum_{n=b+1}^{L} \frac{r_n}{\log_b n}, \tag{1.12}$$

where r_n indicates the relevance of the n-th ranked object ($r_n = 1$ for relevant objects, otherwise 0) and b is a persistence parameter (typically $b = 2$).

Rank-biased Precision (RBP) RBP assumes that users always examine the first object and progress to the next one with probability p, stopping with probability $1 - p$ [198]:

$$RBP = (1 - p) \sum_{n=1}^{L} r_n p^{n-1}. \tag{1.13}$$

1.5.3.2 Diversity and Novelty

Even a relevant recommended object has little value if it is already known. To complement accuracy-focused metrics, several diversity and novelty metrics have been proposed [193, 362].

Diversity Diversity measures the extent to which recommended objects are different from one another. It can be analyzed at two levels:

- **Inter-user diversity:** Measures the difference between recommendation lists for different users.

- **Intra-user diversity:** Measures the variety of objects within a single user's recommendation list.

Inter-user diversity is quantified using the Hamming distance [361]:

$$H_{ij}(L) = 1 - \frac{Q_{ij}(L)}{L}, \tag{1.14}$$

where $Q_{ij}(L)$ is the number of common objects in the top-L lists of users i and j.

Intra-user diversity is measured using object similarity $s(o_\alpha, o_\beta)$ [363]:

$$I_i(L) = \frac{1}{L(L-1)} \sum_{\alpha \neq \beta} s(o_\alpha, o_\beta). \tag{1.15}$$

Novelty and Surprisal Novelty measures how different the recommended objects are from what users have already seen [310]. A simple way to measure novelty is by computing the average popularity of recommended objects:

$$N(L) = \frac{1}{ML} \sum_{i=1}^{M} \sum_{\alpha \in O_i^R} k_\alpha, \tag{1.16}$$

where O_i^R is user i's recommendation list and k_α is object α's popularity. Lower $N(L)$ implies higher novelty.

1.5.3.3 Coverage

Coverage measures the percentage of objects that an algorithm can recommend:

$$COV(L) = \frac{N_d}{N}, \tag{1.17}$$

where N_d is the number of distinct objects in all top-L recommendation lists. High coverage implies diverse recommendations [41, 179].

1.5.3.4 Mean Average Precision (MAP)

MAP is a widely used top-N evaluation metric that measures the overall ranking quality of a recommendation list. It computes the mean of the Average Precision (AP) values over all users, thereby capturing both the relevance and order of recommended items. The metric is defined as:

$$MAP = \frac{1}{|U|} \sum_{u=1}^{|U|} AP(u),$$

where $|U|$ is the total number of users and $AP(u)$ is the Average Precision for user u.

The **Average Precision (AP)** at cutoff N is given by:

$$AP@N = \frac{1}{m} \sum_{k=1}^{N} Precision(k) \times rel(k),$$

where:

- m is the total number of relevant items for user u,

- $Precision(k)$ is the precision at rank k,

- $rel(k)$ is an indicator function equal to 1 if the item at position k is relevant, and 0 otherwise.

1.6 Application areas of recommendation systems: state of the art

This section aims to examine how the technologies and recommendation models for the different recommendation systems mentioned above are researched and applied in accordance with the traits and objectives of the real service industry. According to earlier researchs, the following

service sectors have made use of the recommendation system: streaming, social networking, tourism, e-commerce, healthcare, education, and academic information. The list of services that are mostly utilized in the recommendation system that will be discussed in this part is visually summarized in the figure 1.6.
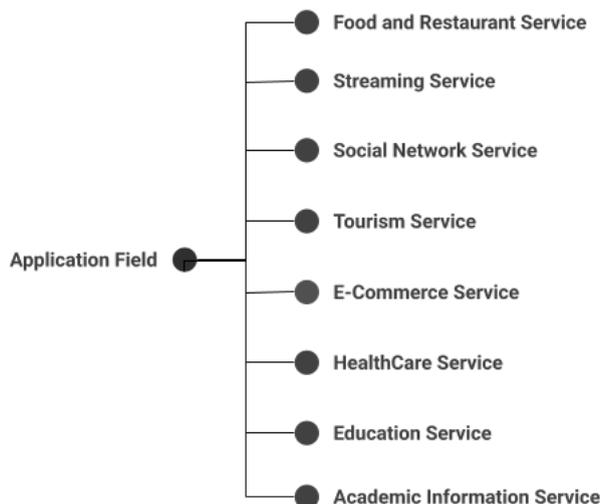
FIGURE 1.6: Application Fields.

1.6.1 Recommendation System in Food

Food recommendation systems have evolved significantly, incorporating various methodologies to personalize dietary suggestions based on user preferences, health conditions, and contextual factors.

In early research, Agapito et al. [7] developed DIETOS, a system designed to provide personalized nutritional recommendations using health profiles based on real-time medical questionnaires, aiding individuals with chronic diseases by leveraging a curated catalog of typical foods. Similarly, Huang et al. [117] introduced a grocery and gourmet food recommendation system by analyzing user opinions from Amazon.com, employing predictive models such as linear regression and SVD++ to tailor suggestions based on user taste preferences.

More advanced approaches emerged, such as Khan et al. [140], who proposed a health-aware recipe recommendation system using Ensemble Topic Modelling (EnsTM) techniques, offering multiple recommendation strategies and demonstrating potential for promoting healthier eating habits. Pecune et al. [226] developed Cora, a conversational system that delivers recipe recommendations while focusing on rapport-building and user engagement through interactive dialogue. Another study by Pecune et al. [225] introduced a system that balances personalization with health-conscious recommendations, leveraging collaborative filtering techniques to rank recipes based on user feedback and health tags.

Hybrid approaches integrating multiple recommendation strategies were explored by Dhyani and Ojha [69], who proposed a model combining Content-Based Filtering and Collaborative Filtering to suggest restaurant dishes based on user taste and location preferences, demonstrating high user satisfaction. Similarly, Sreenivasa et al. [285] presented a meal planning system

tailored to individual health profiles using MERN stack technologies, incorporating BMI and BMR calculations for personalized diet plans supported by certified nutritionists.

Deep learning techniques have been increasingly applied in food recommendations. Rostami et al. [249] proposed a novel hybrid food recommender system that integrates graph clustering and deep learning to address limitations like ignoring ingredients, time factor, cold-start issues, and community aspects. The model combines content-based and user-based recommendations while incorporating time and community dynamics. Experiments on the Allrecipes.com dataset show it outperforms state-of-the-art methods across metrics such as Precision, Recall, F1, AUC, and NDCG. Metwally et al. [196] introduced a system for learning personal food preferences using embeddings derived from users' food logs. By modeling food consumption as sequential patterns, the approach captures contextual relationships among food items. This method leverages the USDA's Food and Nutrient Database for Dietary Studies (FNDDS) to identify commonly consumed foods through vector similarities.

Several studies have focused on health-driven food recommendations. Iwendi et al. [122] developed a framework incorporating deep learning models such as LSTM to recommend personalized nutritional plans based on health-related data collected via IoT, achieving a high accuracy of 97.74%. Sowah et al. [283] designed a system for diabetic patients by integrating TensorFlow-based food classification, KNN-based meal recommendations, and a chatbot for health monitoring, achieving over 95% accuracy in calorie intake classification. Ünal and Çilgin [44] proposed a web-based expert system utilizing Prolog-based rule engines to assist dietitians in meal planning based on Turkish dietary habits and BMI calculations.

Demographic-specific recommendations have also been explored. Princy et al. [235] developed a hybrid recommendation system combining content-based and collaborative filtering to provide healthy dietary options for women based on eating habits and nutritional needs. Sambola et al. [192] introduced a knowledge-based system using semantic technologies to recommend dietary plans for users with varying obesity levels, achieving 87% accuracy in aligning with expert recommendations. Starke et al. [309] introduced the "Cholesterol Factor" metric to balance the healthiness and accuracy of recipe recommendations using collaborative filtering, with minimal accuracy trade-offs.

Advanced methodologies integrating ontologies and multi-criteria decision analysis have also been applied. Subramaniyaswamy et al. [291] leveraged an ontology-based hybrid filtering system to align health and nutrition information with climatic conditions for tourism recommendations. Chaturvedi et al. [45] implemented a deep learning-based mobile application utilizing Mask Region-based Convolutional Neural Network (R-CNN) for food image recognition to provide nutritional insights. Toledo et al. [307] introduced a daily meal planning framework integrating multi-criteria decision analysis (MCDA) and optimization to ensure both nutritional balance and personal preferences.

Other hybrid approaches include Chavan et al. [46], who incorporated user preferences, calorie restrictions, and dietary labels to enhance efficiency. Gorbonos et al. [90] developed the NutRec algorithm, leveraging neural networks to model ingredient interactions and proportions within recipes. Pawar et al. [222] presented NutriCure, a disease-based food recommendation system considering user health data, preferences, and dietary restrictions using KNN algorithms and web-scraped nutrition datasets.

In restaurant recommendations, Gupta et al. [98] proposed a system that personalizes food suggestions based on the user's current mood, utilizing Zomato data and employing the K-Means

algorithm for location-based clustering, along with content-based and collaborative filtering techniques. Goyal et al. [91] developed a restaurant recommendation system that leverages food and service rating distributions, incorporating singular value decomposition and collaborative filtering to enhance recommendation accuracy, with performance evaluated using the RMSE metric.

Keshav et al. [137] introduced a personalized food recommendation application leveraging machine learning to generate tailored suggestions based on weather conditions, dietary restrictions, and time of day. Their system combines content-based filtering, collaborative filtering, and the K-Nearest Neighbors (KNN) algorithm to improve personalization and engagement.

Table 1.2 summarizes the research related to the recommendation system used in the Food and Restaurant field among the papers collected according to the research criteria of this study.

TABLE 1.2: Research related to recommendation systems used in Food.

Ref	Item Recommended	Developed System	Techniques	Dataset
[249]	Food	Time-aware food recommender system based on Deep Learning and Graph Clustering (TDLGC)	Content-based	Allrecipes.com
[7]	Food	DIETOS: DIET-Organizer System	content-based	Calabrian POD foods, Health Calabrian Food Database
[117]	Food	Food recommender system on Amazon	collaborative filtering -Content-Based Filtering	Amazon website (dataset by Julian McAuleyon)
[140]	Food	A personalized health-aware recipe recommendation	Collaborative filtering, Hybrid recommendation	Recipe corpus
[291]	Healthy Food	ProTrip	Hybrid filtering	India's city climate data, Nutritional dataset with recipe info, User dataset
[122]	Healthy Food	IoMT-Assisted Patient Diet Recommendation System	content-based recommendation	medical data collected from the internet and hospitals
[283]	Healthy Food	Diabetes Management System Using Machine Learning	Knowledge-based approach	Patient and nutrition data from University of Ghana, MyFitnessPal database
[226]	Healthy Food	Cora	Conversational system	healthiness-fillingness food (https:// spoonacular .com/food- api)
[225]	Healthy Food	A Recommender System for Healthy and Personalized Recipe Recommendations	Collaborative filtering	allrecipes .com
[80]	Healthy Food	Health-aware Food Recommender System	hybrid recommendation	survey
[69]	Healthy Food	A food recommendation approach that will take flavor	Hybrid filtering	ZOMATO website
[285]	Healthy Food	/	Content-based filtering	genereted Data personalized meal plans.
[196]	Healthy Food	Learning Personal Food Preferences via Food Logs Embedding	Content-based filtering	U.S. Department of Agriculture's Food and Nutrient Database for Dietary Studies (FNDDS).

Ref	Item Recommended	Developed System	Techniques	Dataset
[44]	Healthy Food	a web-based expert system in the field of nutrition with a rule-based system approach.	Content-based.	Generated Data
[204]	Healthy Food	The Diet Recommendation System.	Content-based.	Created Data
[235]	Food	A knowl edge-based diet recommendation system.	hybrid recommendation	Data collected
[192]	Food	A knowledge-based diet recommendation system.	knowledge-based recommendation	-Allrecipes.com - foodRecSys-V1
[309]	Healthy Food	The Cholesterol Facto.	- collaborative filtering -content-based -hybrid methods	Allrecip es.com
[45]	Healthy Food	Food Recognition and Nutrition Estimation Using Deep Learning.	collaborative -content-based -hybrid recommendation	Created Data
[307]	Healthy Food	Daily meal plan recommendations.	Content based	Created Data
[46]	Healthy Food	A Recommender System for Healthy Food Choices	Content-based, Collaborative filtering, Hybrid recommendation	-foodRecSys-V1 (Kaggle.com) -AllRecipes .com
[90]	Healthy Food	NutRec: Nutrition Oriented Online Recipe Recommender.	hybrid recommendation	-Allrecipes .com -Yummly .com
[222]	Healthy Food	Nutricure: A Disease-Based Food Recommender System.	Hybrid filtering	Data Collected
[98]	Restaurant	Mood-Based Food Recommendation System	Content-based, Collaborative filtering	Zomato, Food choices
[91]	Restaurants and popular dishes	Restaurant Recommendation System	Collaborative Filtering	Kaggle
[137]	Food	Smart Dine-in: A Personalized Food Recommendation System	Content-Based, Collaborative Filtering	/

1.6.2 Recommendation Systems in Streaming Services

In the early 2000s, recommendation systems in the streaming service industry primarily relied on Content-Based Filtering (CBF). However, with the rise of Web 2.0, research shifted towards Collaborative Filtering (CF) due to the inefficiencies of CBF in handling the vast amount of rich content available on streaming platforms [29, 148]. Streaming services categorize content by genre, artist, and cast, enhancing user navigation [191]. Early research leveraged text mining techniques to analyze users' viewing histories for personalized recommendations.

In 2013, Odić et al. [211] applied ontology-based text mining to user video histories, integrating situational context for improved recommendations. Their approach captured semantic relationships between user preferences and contextual factors, enhancing accuracy.

To address computational inefficiencies, Barragáns-Martínez et al. [28] introduced a hybrid recommendation model in 2010 using Singular Value Decomposition (SVD) to mitigate scalability issues and data sparsity. Later, in 2020, Walek et al. [319] combined SVD with Fuzzy Logic to improve movie recommendations, achieving 81% Precision, 83% Recall, and an F-measure of 82%.

In music streaming, Wang et al. [330] extracted audio characteristics such as melody and rhythm through text mining to enhance recommendations. Their hybrid model, integrating neural networks, outperformed traditional CBF with a lower RMSE (0.255 vs. 0.270). Similarly, McFee et al. [191] proposed a hybrid model analyzing audio similarity, expanding recommendations beyond a user's immediate preferences.

Recent studies have further refined recommendation approaches. Seo et al. [270] and Bogdanov et al. [34] explored content-based filtering using audio features, while hybrid models incorporating collaborative filtering were developed by Vall et al. [316] and Huh et al. [118]. Colombo et al. [56] extended this by leveraging user evaluation data to improve prediction accuracy.

In video streaming, Sankalp et al. [263] compared CBF and CF, highlighting that CBF excels with limited data, while CF performs better with extensive user behavior data. They concluded that the effectiveness of each method depends on the available dataset and recommendation goals. Meanwhile, Khan and Koffka [139] integrated Fuzzy Logic into adaptive streaming, allowing recommendation systems to dynamically adjust to changing user preferences and contextual factors, enhancing user satisfaction.

The rise of streaming platforms like Netflix, YouTube, and Spotify has revolutionized content consumption, requiring advanced recommendation systems to handle the vast content libraries. By analyzing user behavior and consumption patterns, these systems deliver highly personalized suggestions, enhancing user satisfaction and engagement. With tailored recommendations, users can easily discover new content that matches their interests, improving retention rates and time spent on the platform. As a result, recommender systems are crucial for maintaining competitiveness and fostering long-term customer loyalty in the streaming service industry. Table 1.3 summarizes these research contributions in the streaming service domain.

TABLE 1.3: Research related to recommendation systems used in Streaming Service.

Ref	Item Recommended	Developed System	Techniques	Dataset
[211]	Movies	Ontology-based Recommendation	Hybrid filtering	User Viewing History
[28]	TV Programs	a Web 2.0 TV program recommendation system	Hybrid filtering	TV Program Data
[191]	Music Tracks	Audio Similarity-based Recommendation	Hybrid (Collaborative + Content-Based Filtering)	Last.fm, CAL10K
[319]	Movie	Hybrid Recommendation Model	Hybrid Recommendation	MovieLens
[34]	Music Tracks	semantic audio content analysis and visualization to enhance music recommendation.	Content-Based Filtering	Audio Features + User Data
[330]	Music Tracks	a content-based and hybrid music recommendation using deep learning	Hybrid (Content-Based + Neural Networks)	Million Song Dataset (MSD)
[157]	Music Tracks	Classical Music Recommendation	/	Classical music data
[29]	Music Tracks	Netflix's baseline recommendation system.	Collaborative + Content-Based Filtering, Hybrid Recommendation	Netflix Prize Dataset
[56]	Movie	RecomMetz	Hybrid Recommendation	online movie

Ref	Item Recommended	Developed System	Techniques	Dataset
[316]	Music	Feature-Combination Hybrid Recommender Systems for Automated Music Playlist Continuation	Hybrid recommendation	Art of the Mix6 and 8tracks,7
[263]	Video	Video Streaming Service Recommendations	Content-Based Filtering, Collaborative Filtering	/
[139]	Video	Adaptive Video Streaming Recommendation	Fuzzy Logic-based Filtering	/

1.6.3 Recommendation Systems in Social Networks

Social networks such as Facebook, Instagram, Twitter, and LinkedIn enable users to connect, share daily experiences, and engage in various activities [102]. The exponential growth in user-generated content has made it feasible to extract valuable insights for recommendation systems. These platforms collect likes, comments, and user ratings, which serve as crucial inputs for personalized recommendations. By leveraging these interactions, social networks extend beyond direct friendships, utilizing collaborative filtering and hybrid models for item and friend recommendations [167, 313]. However, collaborative filtering faces challenges such as sparsity, cold-start problems, and the gray sheep issue [332], necessitating advanced approaches.

In 2014, Kim et al. [144] introduced TWILITE, a Twitter recommendation system that employed matrix factorization with collaborative filtering for follower suggestions. To address collaborative filtering's limitations, the study incorporated a probabilistic Latent Dirichlet Allocation (LDA) model to recommend tweets based on user interests. The model demonstrated improved Recall, Precision, and hit-rank index compared to baseline approaches. Two years later, in 2016, Yang et al. [341] enhanced this approach by integrating a Trust model within collaborative filtering, ensuring that recommendations were based on highly trusted users. Their method, tested on four large datasets and compared against PMF, SoRec, RSTE, and SocialMF, outperformed existing techniques, particularly in recommending items to cold-start users.

As social networks evolved, researchers explored hybrid recommendation models to improve accuracy and personalization. In 2019, Amato et al. [19] introduced a hybrid system integrated text mining to analyze user preferences, emotional in text comments, and behavioral data such as previous logs. Their model clustered similar items, enabling more effective user-centered recommendations. Similarly, Capdevila et al. [42] incorporated geographic location data and full-text analysis from social networking sites using text mining techniques. Their hybrid model not only provided personalized item recommendations but also suggested relevant locations. Evaluated using the AUC metric, their system achieved scores of 0.6566 for user-item recommendations and 0.6044 for non-paired recommendations, surpassing traditional content-based and collaborative filtering models.

More recently, sentiment analysis has been integrated into recommendation systems to enhance user experience. In 2020, Dubey et al. [71] developed an opinion lexicon combined with machine learning-based sentiment analysis to extract meaningful insights from tweets. By aligning recommendations with user sentiments, the study demonstrated improved user satisfaction and relevance. Further refining this approach, Hossain et al. [114] in 2024 analyzed user interactions on Facebook and Twitter to assess engagement patterns over time. Their hybrid recommendation

model leveraged collaborative filtering and post category values to personalize recommendations effectively, achieving an NDCG score of 0.60 and a Hit Rate (HR) of 0.80 for the NeuMF model.

In the same year, Gupta [97] examined the real-world impact of hybrid recommendation systems on social media engagement. Over six months, user interactions significantly increased: likes rose by 12.815%, plays by 124.159%, and stream time by 117.349%. The study also observed notable improvements in comments 5.580%, shares 59.825%, and returning users 287.704%, highlighting the system's role in enhancing user retention and personalization.

Another innovative approach was proposed by Chen et al. [50], who introduced a social influence learning model to uncover key user relationship patterns. Their method examined social influence through diversity, disentanglement, and implicit interactions, employing a layerwise graph-enhanced variational autoencoder to reconstruct user neighborhoods. A graph attentive network further identified influential neighbors, enhancing recommendation quality. Experiments on three benchmark datasets demonstrated the superiority of this model over existing approaches.

Recommender systems play a pivotal role in streaming services by analyzing user-generated content, such as viewing history, likes, and comments, to offer personalized content suggestions. As streaming platforms gather vast amounts of data from user interactions, these systems enhance user engagement by providing relevant recommendations based on preferences and behaviors. This personalization not only improves the overall user experience but also boosts retention rates by continuously delivering content that aligns with individual tastes. Consequently, recommender systems help streaming services maintain competitive advantage and drive user loyalty. Table 1.4 summarizes the research related to the recommendation system used in the Social Network.

TABLE 1.4: Research related to recommendation systems used in Social Network.

Ref	Item Recommended	Developed System	Techniques	Dataset
[102]	Social connections	A social network-based recommender system (SNRS)	Hybrid Filtering	Yelp
[313]	Social media content	Collaborative Filtering Model	Content-based Filtering	Twitter data
[167]	Friends and items	TrustWalker	Hybrid Filtering	data collected from Cyworld
[341]	Social connections	Trust-based Recommendation Model	Collaborative Filtering	Large-scale social network data
[144]	Content	TWILITE	Content-based filtering	Twitter data
[19]	Social media content	SOS: a multimedia recommender system for online social networks	Hybrid Recommendation System	Flickr data
[42]	Items and locations	GeoSRS	Hybrid Recommendation	Foursquare data
[71]	Tweets	Improved Opinion Lexicon with Sentiment Analysis	Hybrid recommendation	Twitter Data
[114]	Social media content	SocialRec	Hybrid (Collaborative + Content-Based Filtering)	Social media platforms
[97]	Audio	Real-world Social Media Recommender	Hybrid (Content-Based + Collaborative Filtering)	Social Media Platform Data

Ref	*Item Recommended*	*Developed System*	*Techniques*	*Dataset*
[50]	Social media content	Social Influence Learning Model	Hybrid Recommendation	LastFM, Flickr, Yelp

1.6.4   Recommender System in Travel

With the growing demand for travel, recommendation systems have become increasingly important in suggesting destinations, routes, and transportation options. These systems utilize situational data from social networks, such as reviews, location, time, and weather, enhancing tourism-related recommendations. Social networks store users check-in data and the locations of their uploaded posts, serving as valuable datasets for recommending tourist attractions and travel routes [138, 296].

Content-based filtering has been widely explored in travel recommendation systems. Srisawatsakul et al. [286] leveraged machine learning with the Google Cloud Vision API to extract user preferences from Instagram photos, providing personalized travel recommendations using the Vector Space Model, Cosine Similarity Index, and TF-IDF for similarity calculations. Their system, validated through a user study with 42 participants, demonstrated high precision in recommendations.

Several studies have combined multiple recommendation techniques to improve accuracy and personalization. Kesorn et al. [138] proposed the Personalized Tourism Information Service (PTIS), which integrates hybrid filtering to analyze Facebook check-in data, achieving an average precision of 87.75%. Similarly, Sun et al. [296] applied spatial clustering to geo-tagged Flickr photos to rank key tourist destinations and recommend optimized travel routes by considering destination popularity and road length.

Building on hybrid approaches, Abbasi-Moud et al. [1] introduced a context-aware tourism recommendation system incorporating text mining, sentiment analysis, and semantic clustering to derive real-time situational factors like time, location, and weather. Their model achieved superior precision by filtering out disliked words and providing context-driven recommendations. Additionally, Smirnov et al. [282] developed TAIST, a collaborative filtering-based system that integrates ontology-based situational data to optimize travel routes, successfully assisting 1,000 tourists in finding cultural heritage sites.

Collaborative filtering has been extensively used in tourism recommendations by leveraging user similarities. Kanmani et al. [133] applied k-Nearest Neighbors (kNN) to Twitter data, identifying user similarities and recommending nearby points of interest based on precision, recall, and F-score. Nan et al. [205] enhanced recommendation accuracy and efficiency through knowledge-based transfer learning in their Collaborative Mining and Filtering Process (CMFP), demonstrating improved data handling and processing speeds.

Senefonte et al. [269] introduced PredicTour, a system predicting tourist mobility using self-organizing maps (SOMs) and fuzzy C-means clustering, effectively modeling user travel patterns. Noorian et al. [209] extended collaborative filtering with deep learning, integrating Long short-term memory (LSTM) and Bidirectional Encoder Representations from Transformers(BERT) to analyze past travel sequences and user opinions from social media. Their hybrid approach outperformed state-of-the-art methods in F-score, nDCG, RMSE, and MAP.

Hybrid models integrating deep learning and artificial intelligence (AI) techniques have gained attention in recent years. Al et al. [11] combined big data, AI, and operational research to develop a tourism recommender for Morocco's Daraa-Tafilalet region, offering personalized itinerary planning. Alrasheed et al. [15] proposed a multi-level tourism recommender incorporating dual recommendation procedures, ensuring refined rankings tailored to user needs.

Javadian et al. [124] introduced The Hybrid Offer Ranker (THOR), a transportation recommender predicting user travel preferences via binary classification and clustering algorithms, addressing the cold-start problem by grouping users with similar profiles. Noorian et al. [208] developed BERTSeqHybrid, a deep-learning model integrating BERT, asymmetric schemas, and topic modeling for sequential POI recommendations, significantly improving user-user similarity calculations.

Wu et al. [336] advanced travel mode recommendations by incorporating transportation engineering techniques with a gradient boosting tree model trained on navigation app behavior. Their hierarchical behavior structure captured multi-scale features, optimizing supervised learning outcomes. Finally, Liu et al. [171] proposed the Time-perceived Dynamic Self-Attention Model (TADSAM), which extends self-attention mechanisms to analyze complex check-in records. By segmenting check-ins into time windows and applying personalized weight calculations, TADSAM effectively captures temporal patterns and enhances POI recommendations.

Social network-based recommendation systems have become crucial in the travel service industry by integrating situational data such as user reviews, location, time, and weather from Social network, enhancing personalization. These systems leverage social network data, including check-ins and geotagged posts, to offer tailored travel recommendations, improving the overall customer experience. By understanding user preferences and behaviors, recommender systems help suggest destinations and routes that align with individual interests, fostering greater customer satisfaction and loyalty. Moreover, they encourage repeat visits to popular destinations, reinforcing long-term engagement in the travel sector. Table 1.5 summarizes the research related to the recommendation system used in the Travel field.

TABLE 1.5: Research related to recommendation systems used in Travel.

Ref	Item Recommended	Developed System	Techniques	Dataset
[286]	Tourist attractions	Instagram-Based Tourism Recommendation System	Hybrid Filtering	Instagram data
[138]	Tourist destinations	Personalized Attraction Recommendation System for Tourists Through Check-In Data	Hybrid Recommendation	Facebook data
[296]	Travel routes	Road-based travel recommendation using geo-tagged images	Content-Based Filtering	Flickr data
[1]	Tourist destinations	Tourism Recommendation System Based on Semantic Clustering and Sentiment Analysis	Hybrid Recommendation	TripAdvisor platform
[133]	Travel destinations	Twitter-Based Travel Recommender	Collaborative Filtering	Twitter user data
[205]	Travel recommendations	Collaborative Mining and Filtering Process (CMFP)	Collaborative Filtering	User travel logs and preferences
[269]	Tourist mobility patterns	PredicTour	Collaborative Filtering	Location-based social networks (LBSNs)

Ref	Item Recommended	Developed System	Techniques	Dataset
[209]	Points of Interest (POIs)	a Neural hybrid trip RS	Collaborative Filtering	Social media data
[282]	Tourist destinations	TAIS	Hybrid Recommendation	Smart-M3 platform
[312]	Travel routes	A personalized route recommendation service for theme parks using RFID information and tourist behavior	Hybrid recommendation	RFID data collected
[11]	Personalized trip itineraries	Hybrid Tourism Recommender for Daraa-Tafilalet	Hybrid Recommendation	Tourist visit data for Morocco's Daraa-Tafilalet region
[15]	Personalized travel destinations	A Multi-Level Tourism Destination Recommender System	Hybrid (Collaborative Filtering, Content-Based)	Tourism dataset
[124]	Transportation offers	The Hybrid Offer Ranker (THOR)	Hybrid Recommendation	User travel behavior and purchase data
[208]	Tourist destinations and itineraries	BERTSeqHybrid	Hybrid Recommendation	Yelp, Flickr
[336]	Travel modes	Proactive Travel Mode Recommendation	Hybrid Recommendation	Navigation app historical data
[171]	User decision-making activities	TADSAM (Time-perceived Dynamic Self-Attention Model)	Hybrid Recommendation	Foursquare, Gowalla

1.6.5 Recommendation Systems in E-Commerce

Traditionally, the majority of purchases were made in offline shops for clothing, food, and books. However, with the rise of digital platforms such as Amazon, eBay, and Alibaba, consumer behavior has shifted towards e-commerce. These platforms offer consumers a vast range of products and sellers a convenient sales channel. The COVID-19 lockdowns further accelerated this transition, as restrictions on physical stores led to a surge in online shopping, significantly expanding the variety of items available [78].

E-commerce platforms leverage extensive user data to enhance customer experiences and drive business growth. They employ recommendation systems to analyze user information, including demographic details such as gender and age group, to predict preferences accurately [78]. In addition, research has explored utilizing user-generated opinions shared in Virtual Communities (VCs) within e-commerce platforms to refine recommendations [180]. Moreover, modern e-commerce systems incorporate tracking data, such as mouse movements and keyboard actions, to analyze preferences and predict purchase intentions [293]. By combining tracking data with insights from VCs, platforms deliver more personalized and relevant recommendations. Additionally, recommendations can be improved by analyzing the preferences of similar user groups [127].

A key characteristic of e-commerce is that consumers tend to purchase items related to their previous choices, making Collaborative Filtering and Hybrid recommendation models widely adopted [265]. Gong [89] employed user clustering technology within a Collaborative Filtering model to identify similar users based on purchased item data, enhancing recommendation accuracy. Experimental results demonstrated that increasing the number of neighbors from 20 to 50

significantly improved performance, as indicated by a lower MAE value. Similarly, Hwangbo et al. [119] integrated offline purchase data with online ClickStream data to address the cold-start problem, leading to improved recommendation accuracy. Their proposed system, K-RecSys, outperformed existing shopping mall recommendation systems, achieving a 9.9% click-through rate compared to 5.8%, and a 12.3% purchase rate versus 8.9% for the traditional approach.

To overcome the limitations of Collaborative Filtering, such as cold-start and data sparsity issues, hybrid models incorporating user reviews and comments from VCs were introduced [111].

Further advancements in mobile e-commerce recommendations were proposed by Guo et al. [96], who developed a system combining neural networks and multi-source data to analyze consumer needs. Their approach achieved an accuracy of 91.23%, surpassing traditional methods 80.01%, with improved coverage rates during high-activity periods such as promotions.

With the increasing complexity of e-commerce platforms, researchers have explored enhancements in digital interface design to sustain user engagement. Sulikowski et al. [292] introduced the PERI framework for evaluating recommendation interfaces. Their study revealed that a vertical layout with subtle blinking visual effects significantly improved purchase commitment and recommendation effectiveness compared to a horizontal arrangement.

Recent studies have focused on integrating advanced machine learning techniques for personalized recommendations. Loukili et al. [178] proposed a recommender system that combines collaborative filtering and content-based filtering to analyze user behavior, purchase history, and product attributes, demonstrating improvements in engagement, satisfaction, and sales. Similarly, Khatter et al. [142] introduced a hybrid system integrating collaborative filtering with textual clustering techniques, enhancing recommendation accuracy by incorporating insights from product descriptions and user preferences.

More recently, Sinha and Gujral [280] introduced for analyzing unstructured data in fashion retail. Their framework, achieved an F1-score of 92.5%, aiding retailers in inventory planning and catalog management. Kanth et al. [134] proposed a machine-learning-based recommender system that optimizes recommendation engines to improve engagement and conversion rates. Meanwhile, Patil et al. [220] proposed a hybrid recommendation system combining collaborative and content-based filtering, utilizing the Walmart Product Rating Dataset to adapt to evolving user interactions, improving user satisfaction.

E-commerce platforms facilitate transactions by providing product details and personalized recommendations using various recommender system technologies. Leading platforms like Amazon, eBay, and Taobao leverage cross-selling and Customer Relationship Management (CRM) to enhance customer experience and loyalty. According to a study in [135], Amazon's recommenders contribute to a 35% revenue increase, adding $135 billion in earnings, while Best Buy saw a 23.7% sales rise with personalized recommendations. Similarly, Alibaba's AI-driven recommenders led to a 70% surge in parcel deliveries, generating $42 million daily . Table 1.6 provides a summary of research studies on recommendation systems applied in the E-commerce sector.

TABLE 1.6: Research related to recommendation systems used in E-Commerce.

Ref	Item Recommended	Developed System	Techniques	Dataset
[89]	Item	A collaborative filtering recommendation algorithm based on user clustering and item clustering	Collaborative Filtering	MovieLens
[119]	Products	K-RecSys	Hybrid Recommendation	Data collected shop management system
[96]	Women's clothing	Mobile e-Commerce Recommendation System Based on Multi-Source Information Fusion	hybrid recommendation	Taobao.com.
[292]	Products	PERI	/	Data collected by Gazepoint Analysis software
[111]	website content	Hybrid Recommendation System	Hybrid Recommendation	realtime data
[178]	products	A recommendation system based on association rules via the FP-Growth algorithm	Content-based Filtering	Online Retail
[142]	Products	Advanced Product Recommendation System	Collaborative Filtering	/
[280]	Fashion product	PAE: LLM-based Product Attribute Extraction for E-Commerce Fashion Trends	content-based Filtering	PDF trend reports from PDF on Google
[134]	products	Personalizing the E-Commerce Recommendation System	Collaborative Filtering	/
[220]	products	Walmart Product Recommendation System	Hybrid Filtering	Walmart Dataset

1.6.6 Recommendation System in Healthcare

With the growing interest in health, the adoption of smart wearable devices has surged due to their seamless compatibility with smartphones and ease of use [311]. These devices efficiently monitor users' biometric data, providing valuable insights into personal health [311]. Smartwatches, for instance, continuously track physiological parameters, assisting individuals in disease prevention and self-diagnosis. Moreover, the vast biometric data collected by these devices contribute to disease-related research and enable precise diagnoses based on specific health conditions [197]. Wearable devices play a crucial role in recommending appropriate treatments, enhancing healthcare research, and improving patient outcomes [240, 357].

Health-related recommendation systems analyze symptom patterns to provide personalized treatment insights. These systems are classified into health recommendation systems for personal health management and e-health systems for professional medical support. Their primary goal is to recommend suitable treatments by considering disease symptoms and progression stages. Content-Based Filtering (CBF) is a widely used approach in health recommendation systems, as it effectively evaluates patient-specific data and disease attributes to deliver personalized treatment suggestions.

Duan et al. [70] employed the CBF paradigm to develop a recommendation system for treatment regimens. This approach used text mining to create a tree structure of item dataset prefixes, generating an item ranking list to assist in patient care management. Similarly, Chen et al.

[49] proposed the Disease Diagnosis and Treatment Recommendation System (DDTRS), which leverages large historical medical data and association analysis algorithms to identify similar cases and provide effective treatment recommendations. The system was evaluated on five indicators: effectiveness, chronergy, side effects, cost-efficiency, and patient satisfaction. Physician feedback revealed that the effectiveness index scored the highest at 4.33, while the economic index was the lowest at 3.24, demonstrating the system's ability to deliver high-quality treatment recommendations.

In professional medical treatment, Collaborative Filtering (CF) is frequently utilized to recommend treatments based on the experiences of patients with similar health conditions. Thong et al. [303] applied fuzzy clustering to compute patient similarities and classify them based on disease characteristics. They developed a medical diagnosis recommendation system using CF, demonstrating superior performance with an average MAE value of 0.395, which was lower than other algorithms, confirming its accuracy in medical diagnosis recommendations.

Beyond diagnosis and treatment, recent studies have explored dietary recommendations based on patient data such as disease, age, gender, weight, and nutritional expectations [122, 146, 343]. Iwendi et al. [122] introduced deep learning techniques, including Logistic Regression and Recurrent Neural Networks, for diet recommendations tailored to patients with the same disease. Among various models, LSTM exhibited superior performance, achieving 98% precision, 99% recall, and 99% F-Measure for the allowed class, and 89% precision, 73% recall, and 80% F-Measure for the disallowed class. Unlike other models, LSTM generated consistently good results across all classes, demonstrating its efficacy.

In the realm of e-health services, recommendation systems based on Content-Based models are employed to provide personalized health content based on individual health data [262, 273]. Wiesner et al. [333] developed a context-aware health information system integrating a CBF model with personal health data from the Personal Health Record System. Utilizing semantic networks and ontology techniques, the system provided individualized health recommendations, enabling non-expert users to manage their health data effectively. Likewise, Sanchez Bocanegra et al. [262] proposed a system that leveraged Text Mining and ontology techniques to curate high-quality health-related video content from YouTube. Evaluated using Precision and NDCG metrics, the system demonstrated high accuracy for over-the-counter and diabetes-related videos, with Precision values ranging from 0.50 to 0.87 and 0.68 to 0.89, respectively, and NDCG values from 0.50 to 0.88 and 0.72 to 0.90. However, hypertension-related videos exhibited lower Precision (0.39–0.62) and NDCG (0.46–0.65) values, highlighting areas for improvement.

More recent advancements have focused on leveraging machine learning techniques to enhance healthcare recommendations. Nanehkaran et al. [206] introduced a medical recommender system using the PhysioNet electronic health record dataset. Their approach employed KNN for disease classification and collaborative filtering for treatment recommendations. By leveraging symptom similarities among patients, the system achieved improved accuracy in diagnosing and predicting chronic diseases. Similarly, Torres-Ruiz et al. [308] developed a patient-centered recommender system integrating semantic and geospatial processing to improve healthcare service delivery. Their Web-GIS-based system provided tailored recommendations based on user profiles and medical specialties, improving accessibility and decision-making.

Furthermore, deep learning approaches have been increasingly adopted in healthcare recommendation systems. Chinnasamy et al. [54] introduced an intelligent Health Recommendation System (HRS) utilizing a combination of the Restricted Boltzmann Machine (RBM) and a Coevolutionary Neural Network (CNN). Developed using TensorFlow and Python, the system demonstrated superior performance in accuracy, precision, recall, and F-measure compared to

existing methods. However, a common challenge in such systems is data sparsity, which can reduce their reliability. Addressing this, Alsaaidah et al. [16] proposed an innovative strategy to enhance recommendation accuracy and overcome data sparsity issues. Experiments on two healthcare rating datasets confirmed the method's effectiveness in handling sparse data, improving user decision-making and recommendation quality.

With the rise of smart wearable technology and its seamless integration with smartphones, user adoption has surged alongside increasing health awareness [311]. Devices like Smart-Watches continuously monitor biometric data, assisting in self-diagnosis and preventive healthcare without requiring medical expertise [197]. These devices also contribute to disease research and diagnosis by collecting valuable physiological data, which aids in recommending appropriate treatments [244, 357]. Health-related recommendation systems leverage this data to analyze symptom patterns and suggest personalized treatment options [244]. Table 1.7 provides a summary of the literature on recommendation systems in the Healthcare domain.

TABLE 1.7: Research related to recommendation systems used in Healthcare.

Ref	Item Recommended	Developed System	Techniques	Dataset
[49]	Disease treatment	Disease Diagnosis and Treatment Recommendation System (DDTRS)	Content-Based Filtering	Large-scale historical inspection datasets
[70]	Patient care management plan	a Clinical Recommender System	Content-Based Filtering	Nursing diagnosis data (Clinical data)
[303]	Medical diagnosis	HIFCF (Hybrid Intelligent Fuzzy Collaborative Filtering)	Hybrid Filtering	Patient medical records
[333]	Personalized health information	Context-Aware Health Information System	Content-Based Filtering	letter repository (provided by the Heidelberg University Hospital)
[262]	Health-related video recommendations	HealthRecSys	Content-Based Filtering	MedlinePlus, Youtube
[206]	Medical diagnoses and treatments	a medical recommender identify and treat chronic diseases using an IoT device	Collaborative Filtering	PhysioNet https://physionet.org/.
[308]	Health services and medical centers	a recommender system of health services	Collaborative Filtering	Mexico City health districts (https://www.aamc.org/cim/).
[54]	Healthcare recommendations	Intelligent Health Recommendation System (HRS)	Collaborative Filtering	the Masked Face-Net dataset
[16]	Healthcare recommendations	health recommendation system to aiding healthcare practitioners and users	Collaborative Filtering	RateMDs, WebMD dataset

1.6.7 Recommendation System in Education

Smart Learning has emerged as a transformative trend in education, shifting from traditional classroom-based learning to e-learning facilitated through online environments [305]. The widespread adoption of smart devices and advancements in wireless networks have enabled smart education to provide access to vast digital resources, allowing personalized learning experiences tailored to individual learners' needs, goals, and interests. This evolution enhances education by aligning with the digital age's evolving learning trends [165, 366].

Educational recommender systems enhance personalized learning by considering learners' knowledge levels and learning styles, optimizing learning efficiency and effectiveness. In early research, Content-Based Filtering (CBF) models were widely applied to recommend learning content based on learners' profiles [52, 279, 320]. Shu et al. [279] proposed a CBF recommendation model that utilizes Neural Network technology to analyze learning resource text data, aligning them with learners' preferences. Their approach, CBCNN, demonstrated superior recommendation accuracy, achieving the lowest MAE and RMSE values of 2.6032 and 3.3841, respectively. Compared to traditional recommendation algorithms, CBCNN outperformed non-kNN models in Precision, Recall, and F-Measure while effectively addressing the cold-start problem. Similarly, Chen et al. [52] introduced an Adaptive Learning System that incorporated Plain Vanilla Systems and a Markov Decision Process-based mathematical framework to analyze data on students and learning materials.

Beyond content-based approaches, Collaborative Filtering (CF) has been extensively utilized to recommend learning content by assessing similarities between learning activities and learners [73, 145, 299, 335]. Dwivedi et al. [73] proposed 'eL-GRS,' a CF-based recommendation framework that personalizes learning content by considering individual learner preferences, learning styles, and knowledge levels. Their experimental results demonstrated superior performance, achieving Precision values between 0.6580 and 0.7243, Recall between 0.7316 and 0.9011, and F-Measure between 0.7316 and 0.7993. Additionally, 'eL-GRS' achieved lower MAE values compared to existing systems, confirming its effectiveness in providing high-quality learning resource recommendations. Further advancing CF techniques, Tarus et al. [299] developed an online learning resource recommendation system integrating ontology techniques with Sequential Pattern Mining (SPM) to capture sequential learning patterns and enhance user-resource similarity. Their hybrid model, combining CF, ontology, and SPM, achieved the lowest MAE value of 0.66, outperforming CF alone (0.76) and 'CF+ontology' (0.69). Moreover, learner satisfaction was highest for the hybrid system at 94%, compared to 76% for 'CF+ontology' and 62% for CF, highlighting its superior recommendation quality.

Smart education research has extended beyond content recommendations to include course selection and college preparation topics, offering students a more comprehensive educational experience [76, 94, 210]. Hybrid recommendation models, which combine multiple techniques, have become predominant in generating personalized curriculum recommendations. Esteban et al. [76] introduced a hybrid multi-criteria lecture recommendation system that integrates CF, considering student ratings and grades, with CBF, incorporating lecture attributes such as professors and course content. Their model outperformed traditional CB and CF approaches, achieving the lowest RMSE value of 0.971 compared to 1.123 for the next best model.

More recently, Ashraf et al. [22] conducted an in-depth review of Educational Recommender Systems (ERS), focusing on course recommendation techniques and parameters. Their study provided a comprehensive taxonomy of factors influencing course recommendations, offering valuable insights into enhancing personalized learning experiences. Timmi et al. [306] further expanded on hybrid recommendation methodologies by combining CBF and CF techniques. Their approach, which integrates user profiles, contextual information, and supplementary data, demonstrated its potential to transform informal education in the digital era by delivering highly relevant educational resources tailored to students' needs.

Recommendation systems in education personalize learning by suggesting relevant courses, study materials, and resources based on students' preferences and progress. Evolving from simple rule-based models to AI-driven approaches, modern systems use deep learning and hybrid techniques to enhance adaptability. As AI advances, these systems will continue to refine personalized

learning experiences, improving engagement and outcomes. According to the research criteria of this study, the research on recommendation systems utilized in the Education is summarized in the table 1.8.

TABLE 1.8: Research related to recommendation systems used in Eduction.

Ref	Item Recommended	Developed System	Techniques	Dataset
[279]	Resources	a content-based recommendation algorithm based on convolutional neural network	Content-Based Filtering	MOOCs
[52]	Learning materials	Recommendation System for Adaptive Learning	Hybrid Filtering	/
[73]	Learning Resources	a collaborative system based on the ULP for effective group recommendations	Collaborative Filtering	/
[299]	Learning resources	A Hybrid Knowledge-Based Recommender System for E-Learning	Hybrid Filtering	/
[76]	Courses	Hybrid course recommendation system	hybrid Recommendation	student, course information gathered from Computer Science Degree at University of Cordoba, Spain
	College preparation topics	Ontology-Based Recommendation System	Hybrid Recommendation	Data collected
[94]	Course selections	PCRS (Personalized Course Recommendation System)	Hybrid Recommendation	data collected from M.Tech Courses in Computer Science offered at BSAR crescent university, Chennai
[165]	Personalized learning resources	Intelligent Recommendation System for Course Selection in Smart Education	collaborative filtering	Data courses and student information from University in China
[366]	Learning support	Smart Education System	Collaborative filtering	The flipped classroom in a middle school of north China
[306]	Educational resources	Educational Video Recommender System	Hybrid Filtering	Data repositories

1.6.8 Recommendation system in Academic Research Services

The rapidly growing volume of academic information requires researchers to invest significant time and effort in finding relevant materials. To address this challenge, recommendation systems have been widely applied in academic information services to assist scholars in accessing useful resources efficiently. A key example is the Digital Library, which enables users to search and utilize diverse digital materials worldwide. University Digital Libraries (UDL) also leverage recommendation systems to support learning, education, and research activities [271, 301].

Beyond facilitating access to academic resources, recommendation systems assist researchers in writing and submitting their work. The primary goal of recommendation systems in this domain is to provide tailored academic content to various users, including research institutions and scientific communities [103, 322]. Given that academic materials primarily consist of textual data, Content-Based Filtering and Hybrid models incorporating Text Mining techniques have been extensively explored to enhance recommendation accuracy and relevance [2, 126, 218].

In 2011, Serrano-Guerrero et al. [271] proposed a UDL-integrated recommendation system that utilizes fuzzy logic for text analysis and a Content-Based Filtering model to enhance the search for digital academic materials. The system collects and analyzes user-generated content from Google Wave to improve recommendation accuracy based on text similarity. Performance evaluation, considering user feedback, showed high Precision, Recall, and F-Measure values of 0.7881, 0.8609, and 0.8197 for user recommendations, and 0.8674, 0.8734, and 0.8693 for resource recommendations, confirming the system's effectiveness.

In 2014, Tejeda Lorente et al. [301] proposed a Hybrid recommendation model for UDL systems, incorporating fuzzy text analysis and a quality assessment of resources to enhance recommendation accuracy. By considering resource quality, the system improved accessibility to relevant research materials. Performance evaluation showed an average F-Measure of 0.6765 and an MAE of 0.7565 when quality was considered, compared to 0.5939 and 0.7823 without it, demonstrating the effectiveness of quality-aware recommendations.

In 2016, Achakulvisut et al. [2] developed a Digital Library system that employs a Content-Based Filtering recommendation algorithm to assist academics in finding scholarly publications in their fields of study with precision and effectiveness. Performance evaluation indicated that this approach significantly outperformed conventional keyword-based algorithms, offering more accurate and relevant recommendations.

In 2010, He et al. [103] introduced a Content-Based Filtering citation recommendation system that leverages context-aware Text Mining techniques. Unlike traditional citation recommendation systems, their approach generates ranked citation lists by analyzing the context of the user's ongoing thesis rather than relying on previously cited works. The proposed system, was extensively evaluated using Recall, Co-cited Probability, and NDCG metrics, outperforming seven other citation recommendation methods across all three metrics.

In 2018, Wang et al. [322] proposed a method for recommending conferences or journals based on thesis abstracts. Their approach demonstrated the capability to suggest the best journal or conference for research in an average of roughly 5 seconds, achieving an accuracy of 61.37%.

Most recently, in 2024, Stergiopoulos et al. [288] proposed a novel multi-staged recommender system (RS) that integrates clustering, graph modeling, and deep learning to handle large-scale academic datasets containing millions of users and items (papers). Extensive experiments were conducted to optimize the system's performance, comparing three versions of the RS using recall and NDCG metrics. The results highlight the system's ability to address real-world challenges and effectively manage large academic datasets. This study demonstrates how a multi-staged RS combining diverse techniques can bridge the gap between research advancements and practical industry applications.

Recommendation systems play a crucial role in academic services by enhancing access to research materials, facilitating thesis writing, and supporting scholarly activities. Digital libraries and university platforms leverage these systems to provide personalized recommendations, improving learning, instruction, and research efficiency [103, 271, 301]. Advanced models, such as hybrid recommendation systems integrating text mining and content-based filtering, ensure that researchers, institutions, and scientific communities receive relevant academic content [2, 218, 322].Table 1.9 summarizes the research related to the recommendation system:

TABLE 1.9: Research related to recommendation systems used in Academic Information.

Ref	Item Recommended	Developed System	Techniques	Dataset
[2]	Scholarly publications	Digital Library System	Content-Based Filtering	library the Society of Neuroscience Conference 2015
[271]	Academic resources	Google Wave-based fuzzy recommender system	Content-Based Filtering	Google Wave
[301]	Research Resources	Recommender system based on quality	Hybrid recommendation	university digital library
[103]	The bibliography	A context-aware citation recommendation system	Hybrid Filtering	CiteSeerX digital library
[322]	Journals or conferences	A content-based recommender system for computer science publications	Hybrid Filtering	web service at http://www.keaml.cn/prs/
[288]	Academic papers	An academic recommender system on large citation data based on clustering, graph modeling and deep learning	Content-based Filtering	Large-scale academic datasets

Numerous web and application services have expanded as a result of the growth and dissemination of the Internet, smart gadgets, and social networking sites. The growth of these services necessitates the development of a range of recommendation systems that may assist users in effectively receiving item information and making judgments in the face of the fast growing volume of item information.

1.7 Conclusion

This chapter provided an overview of recommender systems, covering their fundamental concepts, significance, and application areas. We explored the evolution of these systems, highlighting their role in enhancing user experience across various domains such as e-commerce, entertainment, social media, education, healthcare, and travel. Additionally, we discussed the different recommendation techniques, the challenges they face, and the evaluation metrics used to measure their effectiveness. The insights from this chapter lay the foundation for a deeper exploration of recommender systems. With advancements in machine and deep learning and MCDM MEthods, these systems continue to evolve, offering increasingly accurate and tailored recommendations, which will be discussed in greater detail in Chapter 2.

CHAPTER 2

MACHINE / DEEP LEARNING, AND MULTI-CRITERIA DECISION-MAKING (MCDM) APPROACHES FOR RECOMMENDATION

Chapter contents

2.1 Introduction

A recommender system is a type of information filtering system designed to propose relevant items to users [65]. As the range of available products and services continues to grow, these systems have become integral to various domains such as e-commerce (e.g., Amazon), news platforms (e.g., Yahoo, News Today), music streaming (e.g., Last.fm), travel (e.g., TripAdvisor), movies (e.g., Netflix), and social media (e.g., Facebook). Their role is increasingly vital in enhancing user experience through personalized content delivery. To improve the accuracy and relevance of recommendations, modern recommender systems leverage Machine Learning (ML), Deep Learning (DL), and Multi-Criteria Decision-Making (MCDM) techniques. ML methods analyze user behavior and historical data to infer preferences, while DL models (such as neural networks and transformers) capture complex, non-linear user-item interactions. Additionally, MCDM techniques consider multiple factors, including price, quality, and user preferences, to provide more balanced and refined recommendations.

This chapter is organized as follows: Section 2.2 reviews various ML methodss and their application in recommendation systems. Section 2.3 focuses on DL approaches and their contribution to enhancing recommendation quality. Section 2.4 highlights the role of multi-criteria methods in improving decision-making within recommendation frameworks. Finally, Section 2.5 presents a comprehensive discussion on the integration of ML, DL, and MCDM to optimize recommender system performance.

2.2 Machine Learning (ML) for Recommender Systems

Machine learning has become a cornerstone in the development of recommender systems, transforming how users discover products, services, and content in an increasingly digital world. Unlike traditional recommendation methods that relied on static rules or simple collaborative filtering, machine learning enables systems to uncover complex patterns within vast amounts of data, capturing the subtle preferences and behaviors of users. This approach not only improves the accuracy of recommendations but also adapts in real-time to evolving user interests, enhancing personalization and overall user satisfaction [231]. Consequently, machine learning algorithms (including neural networks, matrix factorization, decision trees, and graph-based methods) have become essential for delivering context-aware, personalized experiences.

2.2.1 Categories of Machine Learning techniques

Machine learning offers several methodologies that power modern recommender systems. These methods are generally classified into supervised, unsupervised, semi-supervised, and reinforcement learning as it is shown in figure 2.1 [14]. In recommender systems, supervised learning is commonly used to predict user preferences based on historical ratings or interactions. Unsupervised learning helps uncover hidden patterns or clusters among users or items, enabling personalized grouping and recommendations. Semi-supervised learning is valuable when only a portion of the data is labeled, using both labeled and unlabeled data to improve recommendation accuracy. Reinforcement learning allows the system to learn optimal recommendation strategies by interacting with users and adapting to their feedback over time [131]. Each type plays a distinct role in enhancing the adaptability, precision, and personalization of RSs.
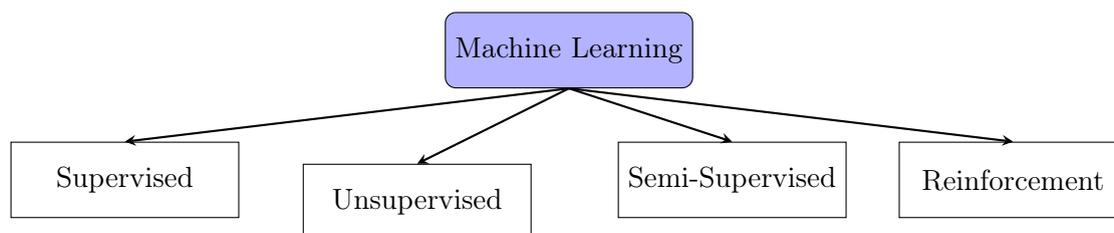
FIGURE 2.1: Types of Machine Learning [14].

2.2.1.1 Supervised Learning in Recommender Systems

Supervised learning methods have been widely applied in recommender systems due to their ability to learn precise user-item relationships from labeled data. These algorithms, such as decision trees, support vector machines, and neural networks, rely on fully labeled training datasets to make accurate predictions. However, their performance depends heavily on the availability and quality of labeled data, making them less effective in situations where such data is scarce or incomplete. Despite this limitation, supervised learning remains a cornerstone of traditional recommender systems, often used in CF and CBF approaches [231]. Figure 2.2 illustrates the typical workflow of supervised learning in such systems.
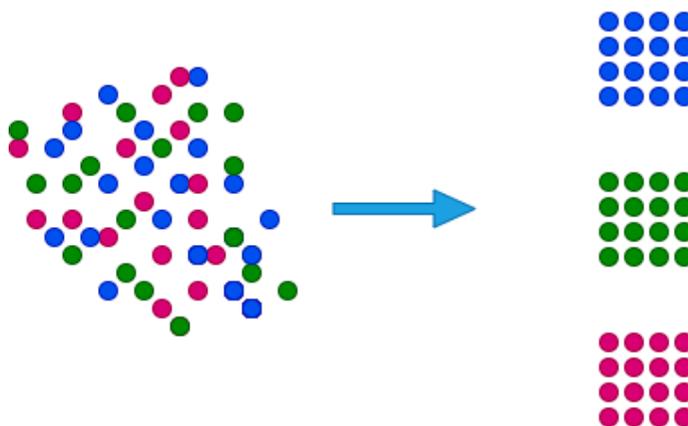
FIGURE 2.2: Supervised Form of Machine Learning [128].

Machine learning encompasses both supervised classification and regression for predictive modeling :

- **Classification** Classification methods are used in RSs to categorize items or users into predefined classes. For example, a movie recommendation system might classify movies into styles or user preferences into different interest groups. Popular classification algorithms, which are used for categorical predictions, include: Naïve Bayes(NB), Logistic Regression (LR), K-Nearest Neighbor (KNN), Random Forest (RF), Support Vector Machine (SVM), Decision Trees (DT). These methods learn from labeled data to assign items to specific categories, making them effective for targeted recommendations. However, their reliance on labeled data can be a limitation when dealing with sparse or noisy datasets.

- **Regression** Regression techniques, on the other hand, aim to predict continuous values, such as user ratings or preference scores. This approach is commonly used in collaborative filtering, where the goal is to estimate a user's potential interest in an item based on past interactions. Regression algorithms, which predict continuous values, include: Simple Linear Regression, Multivariate Regression and Lasso Regression. These methods can provide fine-grained predictions, enhancing personalization, but also require careful tuning to avoid overfitting and ensure generalization.

2.2.1.2   Unsupervised Learning in Recommender Systems

Unsupervised learning, in contrast, does not rely on labeled data, making it particularly useful when clear user preferences are not available. Techniques like clustering, matrix factorization, and dimensionality reduction are commonly used to identify patterns in user behavior and item characteristics without predefined labels. While these methods can reveal hidden structures in data, they often struggle to capture the personalized nature of user interactions, limiting their ability to provide highly tailored recommendations [231].Figure 2.3 visualizes how these techniques operate within recommendation frameworks.
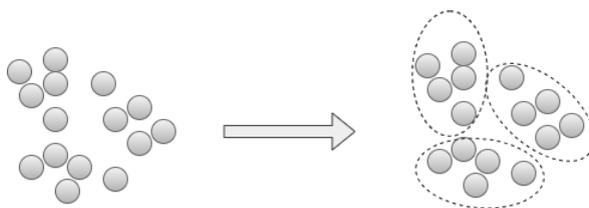
FIGURE 2.3: UNsupervised Form of Machine Learning [128].

Unsupervised machine learning includes techniques like clustering and association for discovering hidden patterns in data:

- **Clustering** Clustering methods are essential in unsupervised recommender systems as they group users or items with similar characteristics without the need for labeled data. Popular algorithms include k-means, hierarchical clustering, and Density-Based Spatial Clustering of Applications with Noise (DBSCAN)Algorithm, Principal Component Analysis (PCA) and Independent Component Analysis (ICA). For example, clustering can be used to segment users based on their past interactions, creating more personalized recommendation groups. This approach helps reduce the dimensionality of the data and discover hidden patterns, but it may struggle with overlapping clusters and varying cluster sizes.

- **Association** Association rule mining is another key technique in unsupervised learning for recommender systems. It focuses on discovering interesting relationships or associations between items in large datasets. For example, the Apriori algorithm is often used to identify items frequently purchased together, such as in market basket analysis. This approach is particularly useful for cross-selling and bundle recommendations, but it can be computationally intensive for large datasets and may generate too many trivial rules without proper filtering.

- **Anomaly Detection**, used to identify unusual patterns or outliers, includes: Z-score Algorithm, Isolation Forest Algorithm.

2.2.1.3 Semi-Supervised Learning in Recommender Systems

Semi-supervised learning represents a hybrid approach, combining the strengths of supervised and unsupervised methods. It addresses the limitations of both by leveraging a small amount of labeled data alongside a larger volume of unlabeled data. This approach reduces the dependency on fully labeled datasets, making it more scalable and cost-effective. By partially guiding the learning process, semi-supervised methods can capture more nuanced user preferences and improve recommendation quality in sparse data environments [231]. This approach has gained significant attention as it balances the need for accurate predictions with the practical challenges of data availability, making it a promising direction for future recommender systems.

Figure 2.4 visually represents this hybrid learning approach in recommender systems.
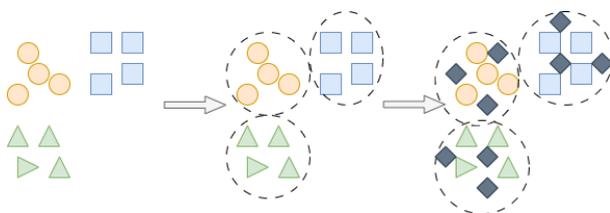
FIGURE 2.4: Semi-supervised Form of Machine Learning [128].

Semi-Supervised Learning is a hybrid approach that leverages both labeled and unlabeled data, encompassing classification through self-training and regression through co-training.

2.2.1.4 Reinforcement Machine Learning

Traditionally, the recommendation problem was framed as a classification or prediction task, but it is now widely recognized that treating it as a sequential decision-making problem more accurately captures the dynamic nature of user-system interactions. This perspective aligns naturally with the framework of Markov Decision Processes (MDPs), making reinforcement learning (RL) a promising approach. Unlike traditional methods like collaborative filtering or content-based filtering, RL can optimize long-term user satisfaction by considering the evolving preferences and engagement over time. Despite its potential, the use of RL for recommendation systems was initially limited by scalability challenges. However, recent advances in deep RL and efficient learning algorithms have made it more practical, enabling systems to personalize experiences at scale and adapt to changing user behaviors. Reinforcement machine learning is illustrated in Figure 2.5.
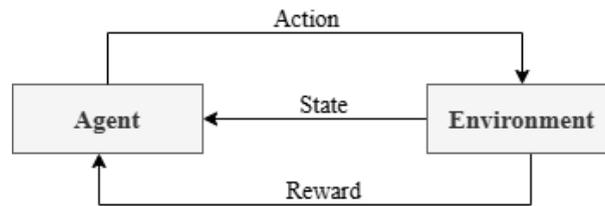
FIGURE 2.5: Reinforcement Learning [128].

Reinforcement Learning is categorized into Model-Free approaches, such as policy optimization and Q-learning, and Model-Based techniques, which involve explicitly learning or utilizing an existing model, including learning the model and using a given model. In the literature, a wide variety of machine learning algorithms have been proposed, typically classified into four main types based on their learning approach: supervised, unsupervised, semi-supervised, and reinforcement learning.

2.2.2   Recommender systems based on ML techniques: State of art

Machine Learning can be broadly categorized into four main types: Supervised Learning, Unsupervised Learning, Semi-Supervised Learning, and Reinforcement Learning, each with distinct methodologies and applications. Figure 2.6 illustrated this.
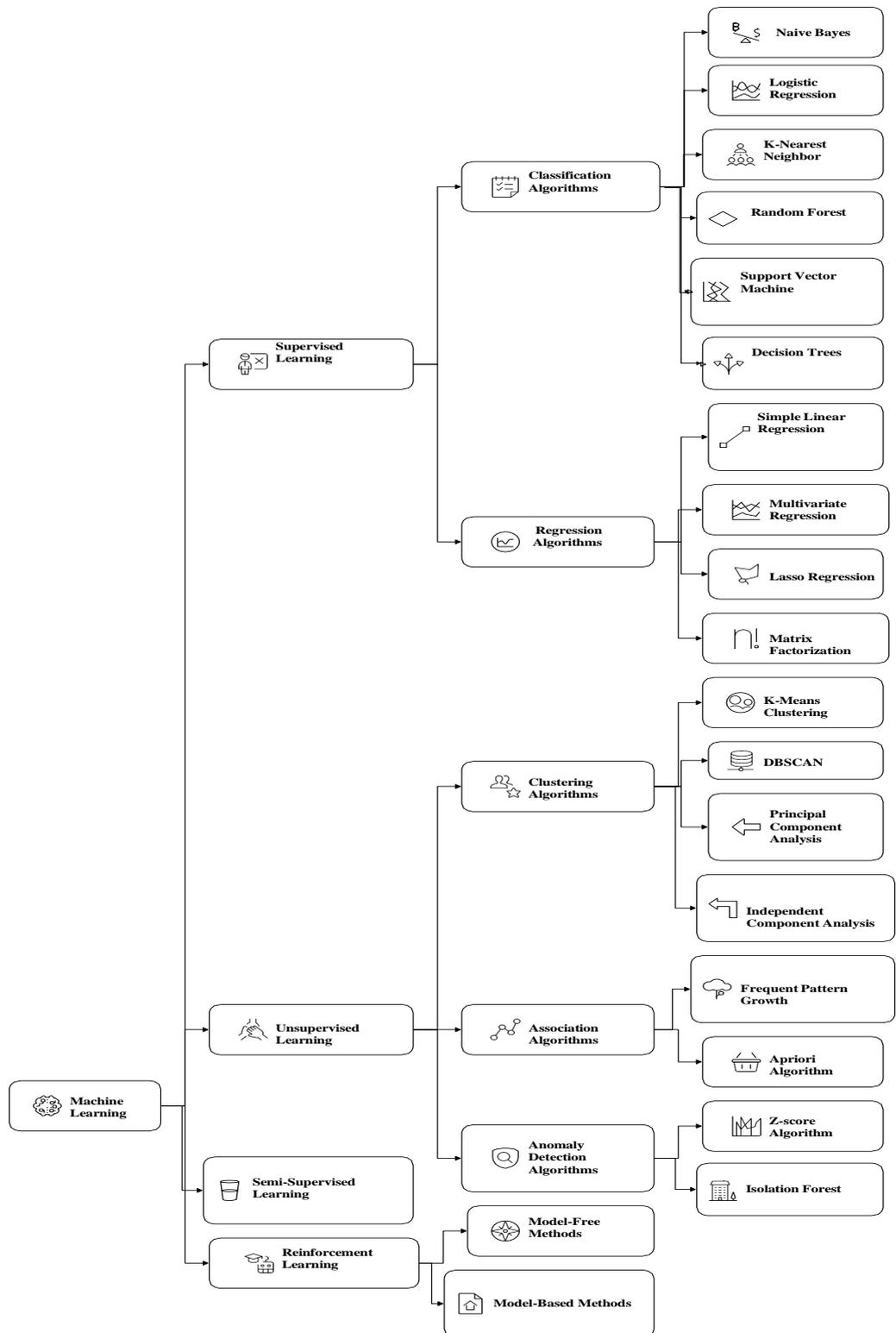
FIGURE 2.6: Machine Learning Algorithms [81].

In this section, we present some of the most widely used machine learning algorithms, particularly those commonly applied in recommender systems.

Matrix Factorization (MF)

Matrix Factorization (MF) is a core linear algebra technique for decomposing large matrices into smaller, more manageable components. It is particularly popular in recommendation systems due to its ability to efficiently capture complex user-item interactions. These systems often rely on user-item rating matrices, which can grow exceptionally large as the number of users and items increases, leading to significant computational challenges. MF addresses this by reducing data dimensionality, enabling faster processing while retaining essential information. This approach supports both supervised and unsupervised learning, making it a versatile choice for modern recommendation algorithms [149, 152].

Liu et al. [170] extended traditional Matrix Factorization (MF) methods by incorporating temporal and social context, recognizing that user preferences evolve over time. Their approach introduced time-aware MF, where recent ratings are weighted more heavily, capturing current user inclinations through exponentially decaying relevance factors. Additionally, social network-aware MF, like the Network Regularized Matrix Factorization (NRMF) method, integrates user connections, assuming that socially linked users share similar preferences. While both approaches show promising results individually, combining temporal and social factors remains a challenging yet potentially impactful direction for future research.

A mood-based movie recommendation approach is proposed in [277], introducing mood-specific movie similarity to enhance conventional Collaborative Filtering (CF) techniques. This technique calculates a mood similarity matrix based on user mood tags, extending standard Matrix Factorization (MF) to incorporate this context. Experimental results on the MoviePilot mood track dataset show that MF method slightly outperforms baseline methods, including Random Walk with Restart and standard MF, suggesting potential for further improvement by integrating additional movie-specific contexts.

Shi et al. [278] extended their mood-specific movie similarity model [277] by incorporating plot-keyword similarity, recognizing that movies with similar plots often evoke comparable viewer responses. This approach, which combines mood and plot contexts, demonstrated improved performance on the MoviePilot mood track dataset using Mean Average Precision (MAP) as the evaluation metric, outperforming standard MF and other baseline methods. However, adding more contextual features could increase computational overhead, highlighting the need for parallel execution to maintain efficiency.

Naïve Bayes (NB)

Naïve Bayes (NB) is a probabilistic supervised machine learning algorithm grounded in Bayes' theorem, a principle of conditional probability. It operates under the "naïve" assumption that features (or attributes) are conditionally independent given the class label. Despite this strong simplification, NB performs effectively in practice due to its efficiency and robustness, making it suitable for large-scale applications. In the context of recommender systems, NB can be leveraged to estimate the probability that a user will prefer or interact with an item based on historical data and contextual attributes (e.g., user profile, item features, or past interactions). The model computes the likelihood of a user's preference by combining the probabilities of

different item attributes, assuming independence among them. This enables NB to handle both binary recommendations (like/dislike, purchase/not purchase) and multi-class categories (different rating levels or item groups).

Bayes' theorem is a foundational statistical approach for supervised learning, offering competitive prediction accuracy with state-of-the-art methods. It relies on a probabilistic model that estimates conditional probabilities from training data, making it effective for classification tasks. Its simplicity and interpretability make it a popular choice in machine learning.

A Bayesian classification-based model for mobile video recommendation is proposed in [62], addressing the challenge of selecting relevant content under resource constraints. The system uses user profiles stored on a recommendation server, incorporating contexts like time, location, and mood to predict video preferences. Future work could explore context relaxation strategies for scenarios with limited user data and assess system accuracy through real-time experiments.

Gupta et al. [99] proposed a context-aware recommendation model combining Naive Bayes and Singular Value Decomposition (SVD) to efficiently predict user preferences. Naive Bayes is used to identify significant contextual attributes, reducing computational costs by filtering less impactful factors, while SVD handles dimensionality reduction to capture high-rating associations. Simulated results for travel recommendations show promising alignment with user preferences, though real-time testing could further validate this approach.

Recommender systems personalize services by learning user preferences through ratings, employing techniques like collaborative filtering and Naïve Bayes. However, they face challenges such as the cold-start problem and slow adaptation to evolving user preferences. To address these limitations, Pronk et al. [236] proposed an enhancement to the Naïve Bayes classifier by combining two user profiles: one automatically learned from rating feedback and another manually constructed, providing greater user control and flexibility in generating recommendations.

K-Nearest Neighbor algorithm (kNN)

K-Nearest Neighbors (KNN) is a widely used approach in Collaborative Filtering for recommendation systems. It identifies a group of similar users for each target user based on similarity measures like cosine similarity, and then predicts user preferences by taking a weighted average of the ratings from the k most similar users [93].

Baltrunas and Ricci. [26], proposed enhancing recommendation accuracy by splitting user-item ratings according to contextual factors. It integrates this approach into collaborative filtering, where KNN is used to find similar users or items within each contextual segment. By leveraging KNN on contextually split data, the system achieves more accurate and personalized.

Chen et al. [51] proposed RegionKNN a hybrid model that integrates clustering with collaborative filtering to enhance scalability and accuracy. KNN is employed to identify the most similar users or services within clustered regions, reducing computational complexity. This region-based KNN approach ensures efficient, personalized web service recommendations. In [355], a group recommendation approach for cyber-physical-social systems is introduced, integrating mobile and social data to infer users' emotional states via sentiment analysis. The method employs kNN for group formation and matrix factorization for preference modeling, achieving notable improvements in recall, precision, and RMSE on the Yelp dataset. Future work may consider bio-inspired learning techniques to further enhance efficiency and effectiveness.

In 2020, Kanmani et al. [133] proposed a context-aware travel recommendation system that uses users current locations extracted from Twitter data via the Twitter API. The system employs collaborative filtering to analyze user preferences, identify similar users, and recommend the nearest point of interest from potential itineraries using kNN algorithm. Its performance is evaluated using precision, recall, and F-score metrics, demonstrating its effectiveness in personalized travel recommendations.

Pawar et al. [222] introduced NutriCure, a disease-based food recommendation system that personalizes diet plans based on users' health data and preferences. They employed KNN for recommendations using a web-scraped dataset of nutrient-rich foods and filtered recipes based on dietary restrictions and disease information. Testing with 100 demo users validated the system's efficiency in providing tailored nutrition recommendations. In a related study, Sowah et al. [283] developed a system for diabetic patients that combines multiple AI algorithms to track and manage their health. The system employs a TensorFlow neural network for food classification, KNN for meal recommendations, and a chatbot for diabetes-related queries, integrating geolocation and blood sugar data. The food recognition model achieved over 95% accuracy in classifying meals based on nutritional value, supporting diabetes management through personalized recommendations.

Support Vector Machines (SVM)

SVM are supervised learning algorithms that classify data by finding the optimal hyperplane that maximally separates different classes. For complex, non-linearly separable data, SVM can use kernel functions to map the data into a higher-dimensional space where it becomes linearly separable. Cortes et al. [57] introduced the concept of support vector networks, which extend this approach to efficiently solve two-group classification problems.

Oku et al. [212] proposed a context-aware recommendation system for restaurants using Support Vector Machines (SVM). They introduce a Context-aware SVM (C-SVM) that incorporates various contextual attributes into the classification process. Additionally, they propose a Context-aware SVM using Collaborative Filtering (C-SVM-CF) that computes user similarity based on their preferences across different contexts. Experiments on the Yahoo! Gourmet dataset show that C-SVM outperforms standard SVM, and C-SVM-CF provides better recommendations in terms of user satisfaction compared to both C-SVM, SVM, and random methods. This approach can be extended by integrating additional contextual attributes for further improvement.

Kahng et al. [130] proposed a ranking-based approach for recommendations under different contextual conditions. They use five types of features: popularity-based, user-based, contextual variables, a combination of user and one contextual variable, and all components together. Experiments with data from Bugs (music streaming) and Foursquare (location-based service) show that Ranking SVM outperforms other methods, such as popularity-based approaches and user-based collaborative filtering. Further context inference techniques and comparisons with other baseline algorithms could enhance the system's efficiency.

SVM-based context-aware recommendation systems are explored in [150], where user preferences are classified as context-independent and context-dependent. These preferences are input to an SVM, which generates recommendations. Experiments on the TripAdvisor dataset demonstrate the effectiveness of this SVM-based approach. This method can be incorporated into collaborative filtering techniques, and experimenting with different SVM variants could further improve the system's accuracy.

a hybrid framework for personalized movie recommendations is proposed in [329]. SVM is
employed to classify and predict user preferences, forming the core recommendation engine.
Combined with improved PSO for parameter optimization, SVM enhances accuracy and per-
sonalization in movie recommendations. Furthermore, Zahálka et al. [350] introduced "City
Melange," an interactive venue recommender. The system leveraged a linear Support Vector
Machine (SVM) to capture semantic information and extract latent topics.

Logistic Regression (LR)

Logistic Regression (LR) is a fundamental linear classification model used to estimate the prob-
ability of a binary outcome based on input features. It maps a linear combination of predictors
to a probability using the sigmoid function and is optimized through numerical methods. In rec-
ommender systems, LR plays a key role in predicting user preferences, such as the likelihood of
a user interacting with or purchasing an item. Its interpretability and efficiency make it suitable
for modeling implicit feedback and click-through rate (CTR) predictions. As a baseline model,
LR is often used to benchmark the performance of more complex recommendation algorithms.

Logistic regression is a widely used statistical method for predicting discrete outcomes based
on both continuous and categorical input variables [324]. In the context of collaborative tag-
based recommender systems (RS), Montañés et al. [199] applied logistic regression to effectively
rank meaningful tags within social networks. Furthermore, this technique has been employed to
assess user trustworthiness and detect potential attacks in collaborative filtering recommender
systems (CFRS). For example, Zheng et al. [358] proposed a method to handle ordinal rating
data more effectively in recommender systems. Ordered Logistic Regression is applied to model
user ratings as ordered categories, preserving the natural order of preferences.

Wang et al.[331] proposed a mobile recommendation system combining Logistic Regression (LR)
and Gradient Boosting Decision Trees (GBDT) to handle noisy user behavior data. It introduces
tailored preprocessing and feature extraction methods for mobile environments. The model is
evaluated on a large-scale real-world dataset from Alibaba. Experimental results show a 2%–36%
improvement in F1-score over baseline methods.

Tian et al.[304] presented a hybrid music recommendation system (LX) combining Logistic
Regression and eXtreme Gradient Boosting (XGBoost) to address data sparsity and nonlinear
feature issues. Traditional collaborative filtering is limited when handling new items, prompting
the need for improved models. The LX model leverages the strengths of both algorithms to
predict user preferences more accurately. Experiments on real music data show improved error
rates and AUC compared to existing methods.

Decision Tree (TD)

Decision trees are flexible, non-parametric methods widely used for classification tasks, offer-
ing interpretability through structured, sequential decisions. They build hierarchies of decision
rules to segment data and achieve class homogeneity at leaf nodes. In recommender systems,
decision trees can model user preferences and item features to generate accurate, rule-based rec-
ommendations. Algorithms like CART and C4.5 efficiently split data to predict user behavior
or item ratings. Their transparency and speed make them valuable for real-time, personalized
recommendation tasks.

The decision tree is a powerful machine learning technique used for making decisions among multiple alternatives. In the context of recommender systems (RS), it is employed to estimate and predict missing user preferences based on available data. Gershman et al. [83] introduced a method where each leaf node recommends a list of items, enhancing scalability. It proposes a new splitting criterion—least probable intersection size for more effective tree construction. Experimental results on the MovieLens dataset demonstrate improved recommendation quality over traditional information gain-based methods.

Golbandi et al. [85] proposed an adaptive bootstrapping method using specialized decision trees that dynamically tailor questions to quickly build user profiles. Experimental results within a movie recommendation platform show that this approach significantly outperforms traditional methods.

Random Forest (RF)

Random Forest (RF) is a robust, non-parametric ensemble algorithm used for both classification and regression, making it suitable for recommendation systems. By aggregating multiple decision trees trained on bootstrapped data and random feature subsets, RF reduces overfitting and enhances generalization. In recommender systems, RF can predict user preferences or ratings by learning complex, non-linear relationships between user and item features. Its ability to handle high-dimensional data and mixed feature types makes it effective in modeling personalized recommendations. RF's interpretability and ease of use further contribute to its popularity in recommendation tasks.

Zhang and Min. [353] proposed a framework using random forest to estimate the probability of user preference for enhances recommendation performance. Building on this, Javadian et al.[124] proposed THOR, a personalized transportation RS that uses RF for binary classification to predict purchase likelihood. THOR addresses the cold-start problem through traveler clustering, enabling context-aware, cohort-specific recommendations with high accuracy.

K-means

The K-means algorithm is an unsupervised clustering method that partitions data into k groups by minimizing intra-cluster variance [183]. It iteratively assigns data points to the nearest centroid and recalculates centroids until convergence [10]. In recommender systems, K-means helps segment users or items into similar preference groups, enabling CF and personalization. By clustering users with shared behaviors, it enhances recommendation accuracy and scalability. Its simplicity and efficiency make it a practical tool for large-scale recommendation tasks.

In 2017, Cenamor et al. [43] developed PlanTour, a tourism recommender system that combines human expertise with automated planning techniques. It uses declarative methods for easier system maintenance and employs k-means clustering on data from Yelp, Google Places, and Minube to generate personalized daily itineraries. The system dynamically adapts to users' real-time context, such as location, activity, and time. PlanTour effectively enhances combinatorial problem-solving in tourism by integrating human recommendations.

Amoretti et al.[20] introduced UTravel, a smart mobility application that provides personalized Points of Interest (POI) recommendations using a Universal Profiling and Recommendation (UPR) approach. UPR employs a hybrid profiling method that combines individual user behavior with similar user patterns through multi-criteria analysis by used UTilités Additives(UtA)

method. The system was evaluated in two phases—first with simulated users to test profiling and clustering accuracy, and then with real users to assess functionality. Results showed strong performance in terms of accuracy, recall, and coverage of recommendations. Yin et al. [346] presented an intelligent platform to improve tourism services and recommendations. K-means clustering is applied to segment users and tourism resources based on feature similarity, enabling personalized services. This clustering-driven approach enhances recommendation accuracy and user experience in tourism e-commerce.

Singular Value Decomposition (SVD)

Singular Value Decomposition (SVD) is a powerful matrix factorization technique used in recommender systems for dimensionality reduction and collaborative filtering. By decomposing the user-item rating matrix R into user and item feature matrices U and V, SVD captures latent factors that explain observed preferences. This decomposition enables the approximation of missing ratings through the formula.

$$r_{ij} = u_i^T \Lambda v_j \tag{2.1}$$

In recommender systems, SVD identifies latent features of users and items, facilitating personalized recommendations based on these hidden factors. The optimization of the loss function through gradient descent ensures accurate prediction of user-item interactions, even with sparse data. SVD is especially useful for handling large-scale datasets, improving recommendation accuracy while minimizing overfitting through regularization. By predicting ratings based on these latent features, SVD enhances the ability of recommender systems to suggest items that align with user preferences.

Gupta et al.[99] introduced a context-aware recommendation model that integrates Naive Bayes for selecting relevant contextual factors and SVD for dimensionality reduction. This combination improves prediction efficiency and accuracy. Simulated travel recommendation results aligned well with user preferences, though real-time evaluation is suggested for further validation.

Recommender systems are also widely applied in education to enhance personalized learning. Teodorescu et al. [302] proposed an SVD-based recommendation system for quizzes to assess learners knowledge in real time using concept maps for graph algorithms. They compared two groups: one receiving randomized quizzes and the other receiving recommended questions. The results showed that students who received recommended questions performed significantly better than those with randomized quizzes. In addition, Bhalse et al. [32] proposed a web-based movie recommendation system that combines collaborative filtering with SVD and Cosine Similarity (CS) to address the sparsity problem. The system generates personalized recommendations by incorporating both user preferences and movie content information.

Principal Component Analysis (PCA)

Similar to SVD, Principal Component Analysis (PCA) is a powerful technique for dimensionality reduction, which can significantly enhance the efficiency of recommendation systems by reducing computational complexity while preserving most of the variance in the data [318]. PCA is a multivariate statistical procedure that transforms a set of possibly correlated variables into a new set of linearly uncorrelated variables called principal components (PCs). These components

are obtained as linear combinations of the original variables and are ordered such that the first principal component captures the maximum variance in the data, the second captures the next largest variance orthogonal to the first. Mathematically, let the dataset be represented as a centered matrix $X \in \mathbb{R}^{n \times p}$, where n is the number of observations and p is the number of variables. The covariance matrix is defined as:

$$\Sigma = \frac{1}{n} X^T X \tag{2.2}$$

The principal components are obtained by solving the eigenvalue decomposition:

$$\Sigma v_k = \lambda_k v_k \tag{2.3}$$

where:

- v_k is the eigenvector corresponding to the k-th principal component,

- λ_k is the eigenvalue representing the variance explained by that component.

Bandyopadhyay et al. [27] proposed a product recommendation model for e-commerce that integrates Principal Component Analysis (PCA) with K-means clustering. In this framework, PCA is employed for dimensionality reduction, enabling the efficient handling of high-dimensional data, while K-means clustering facilitates customer segmentation. This combined approach not only improves recommendation accuracy but also reduces computational cost, thereby helping businesses better understand consumer behavior and provide more personalized product suggestions.

In a complementary direction, Addagarla and Amalanathan. [3] introduced a probabilistic unsupervised learning approach for developing a similar image recommender system in e-commerce. Here, PCA again plays a central role by performing feature extraction and dimensionality reduction, ensuring efficient representation of product images. These reduced feature sets are then utilized to measure similarity among items, allowing the system to recommend visually related products. This method further strengthens recommendation quality, improves user experience, and aids customers in making better purchasing decisions.

Non-negative Matrix Factorization (NMF)

Non-negative Matrix Factorization (NMF) is a matrix factorization technique used in collaborative filtering to uncover latent features that explain user-item interactions in recommender systems. Unlike SVD, NMF constrains user and item feature matrices to be non-negative, aligning better with the intuitive notion of user preferences. It iteratively updates these matrices using multiplicative rules to minimize reconstruction error while preserving non-negativity. Regularization prevents overfitting and improves generalization. By learning latent representations, NMF enhances the recommender system's ability to predict user preferences and generate accurate suggestions.

Li et al. [162] developed a collaborative filtering approach using the NMF recommendation algorithm with a privacy protection mechanism for cloud computing. Their experiments show that the algorithm maintains recommendation accuracy while effectively safeguarding user privacy.

Moreover, Al-Nafjan et al. [12] compared SVD, SVD++, and NMF methods for restaurant rating prediction using location-based social networks (LBSNs). The system was evaluated using RMSE and MAE, where SVD achieved the lowest RMSE, and SVD++ obtained the lowest MAE. Their results demonstrate the effectiveness of matrix factorization techniques in restaurant recommendation systems.

Ensemble learning algorithms

Ensemble learning, particularly boosting algorithms, significantly enhances the performance of recommender systems by combining multiple weak methods to improve predictive accuracy. These methods increase robustness and personalization, especially in complex and noisy user-item interaction data. AdaBoost refines predictions by focusing on difficult cases, while gradient boosting minimizes residuals for more accurate recommendations. XGBoost boosts scalability and accuracy through regularization and parallelism, ideal for large-scale recommendation tasks. CatBoost effectively handles categorical features, aligning well with user preferences and item categories, leading to more relevant and satisfying recommendations.

- Extreme Gradient Boosting (XGBoost)

  XGBoost is a high-performance gradient boosting algorithm that excels in recommender systems by efficiently handling large-scale, sparse, and noisy data. It optimizes predictive accuracy through regularization, parallel processing, and smart handling of missing values. By minimizing a regularized objective function, XGBoost balances model fit and complexity, reducing overfitting. Its iterative learning with residual correction enables more accurate user-item preference modeling. These capabilities make XGBoost ideal for generating fast, scalable, and highly personalized recommendations.

  In [67], employed XGBoost to stock market prediction by framing the problem as a classification task that forecasts the direction of price movement rather than exact values. It leverages XGBoost's strengths in handling non-linear relationships, feature importance, and overfitting control to improve prediction accuracy. Results show that XGBoost outperforms traditional methods in capturing market patterns for directional forecasting. In e-commerce sector, Xu et al. [340] proposed a recommendation system built on the Extreme Gradient Boosting (XGBoost) classifier, leveraging its efficiency in handling large-scale and high-dimensional data. XGBoost captures complex feature interactions to improve prediction accuracy and recommendation quality. Experimental results show that it outperforms traditional machine learning methods in both effectiveness and scalability. Zhou et al. [359] introduced a Multi-Model Stacking Ensemble (MMSE) for personalized commodities recommendation. In this framework, XGBoost is used as the meta-classifier to combine the outputs of multiple ensemble base methods. Experimental results on Alibaba's E-Commerce data show that XGBoost delivers superior accuracy.

  A context-aware location recommendation system is introduced in [274] for tourists, leveraging sequential behaviors and contextual factors. As an alternative, XGBoost captures complex feature interactions without relying on heavy sequence modeling, offering efficiency and scalability. Its strong predictive power leads to improved accuracy in location-based recommendations compared to traditional methods.

  Vemula et al. [317] proposed an aspect-based tourism recommendation system that incorporates multiple features of tourist reviews and destinations. It applies XGBoost to effectively capture non-linear relationships between aspects and user preferences. XGBoost's

ability to manage high-dimensional data and prevent overfitting enhances recommendation accuracy. The results demonstrate that XGBoost outperforms baseline methods in delivering more personalized tourism suggestions.

- Categorical Boosting (CatBoost)

  CatBoost is a powerful gradient boosting algorithm tailored for categorical data, making it highly effective in recommender systems where user and item attributes are often categorical. It uses ordered boosting and symmetric (oblivious) trees to reduce overfitting and improve model stability. By minimizing a regularized loss function, CatBoost enhances generalization and predictive accuracy. Its ability to process raw categorical features without explicit encoding streamlines model training and improves personalization. This makes CatBoost ideal for delivering precise, scalable, and user-centric recommendations.

  Christopher et al. [55] proposed university recommendation systems enhanced with CatBoost for accurate prediction of student–university matches. CatBoost efficiently processes categorical data such as academic background, preferences, and demographics, reducing bias and overfitting. Its role is central in boosting recommendation accuracy, outperforming traditional machine learning methods. In addition, to addressed the challenge of predicting the duration of stay in personalized travel recommendations, [8] used CatBoost, which efficiently handles categorical features and reduces overfitting, making it well-suited for user travel behavior data. Results show that CatBoost enhances prediction accuracy compared to conventional machine learning.

Table 2.1 presents a summary of related research on recommender systems that utilize machine learning methods:

TABLE 2.1: Summary of Machine Learning-Based Approaches in Recommender System Research

Ref	Algorithm / Method	Function	Application Area
[170]	MF	Enhances personalization by integrating temporal dynamics and social influence into Matrix Factorization	Movie
[277]	MF	Enhances collaborative filtering by integrating mood-specific movie similarity from user mood tags	Movie
[278]	MF	Improves recommendation accuracy by incorporating mood and plot contexts, evaluated with MAP while ensuring efficiency	Movie
[62]	Bayesian Classifier	Incorporates contextual information (e.g., location, time) into recommendation process	Mobile services
[99]	Naive Bayes, SVD	Combines Naive Bayes and SVD for efficient, context-aware recommendations with lower computational cost.	Travel
[236]	Naïve Bayes	Merges learned and user-defined profiles for flexible personalization, tackling cold-start and adaptability issues.	MultiMedia
[26]	KNN	Improves recommendation by splitting ratings according to contextual factors before applying similarity search.	Movie

Ref	Algorithm / Method	Function	Application Area
[51]	KNN	Enhances scalability and accuracy by combining clustering with KNN-based similarity search	web service
[355]	kNN, MF	Computes similarity among users in groups to aggregate preferences for collective recommendations.	social/mobile applications
[133]	kNN	Utilizes contextual and location-based similarity to provide timely and relevant social media recommendations	Social media applications
[222]	KNN	NutriCure provides personalized diet recommendations based on health data, preferences, and disease-specific needs.	Disease-based food
[283]	KNN	Classifies patients by medical attribute similarity to predict and manage diabetes risk	Healthcare
[212]	SVM	Classifies and predicts user preferences by incorporating contextual information for adaptive recommendations	Restaurant.
[130]	SVM	Classifies and predicts user preferences by incorporating contextual information for adaptive recommendations.	Music
[150]	SVM	Learns decision boundaries between preferences and context to enhance recommendation accuracy.	POIs
[329]	SVM	Classifies and predicts user movie preferences, optimized with PSO for higher accuracy	Movie
[350]	SVM	Classifies and learns from multimodal features (text, images, interactions) to model user-venue relationships	POIs
[199]	LR	Ranks meaningful tags in social networks for collaborative tag-based recommender systems	Social network
[358]	LR	Detects malicious users in collaborative filtering by evaluating trust scores	Movie
[331]	LR	Captures linear relationships between user features and preferences as a baseline for hybrid modeling	Mobile
[304]	LR, XG-Boost	Models linear relationships between user features and music preferences as a baseline for hybrid predictions.	Music
[83]	DT	Proposes a leaf-node strategy with a new splitting criterion to improve scalability and effectiveness	Movie
[85]	DT	Proposed a dynamic question-asking bootstrapping method to build user profiles rapidly	Movie
[353]	RF	Uses ensemble decision trees to model user–item–context interactions, enhancing robustness and accuracy	Movie
[124]	RF	Applies Random Forest and traveler clustering to provide accurate, personalized transportation recommendations.	Travel
[43]	k-means	To improve combinatorial problem-solving by leveraging human-provided recommendations	Tourism

Ref	Algorithm / Method	Function	Application Area
[20]	k-means	To inform and guide users to POI in order to make tourist mobility smarter	POI
[346]	K-means	Compares traditional and modern cloud platform methods to optimize AI applications in tourism.	Tourism, E-commerce
[302]	SVD	Personalized quiz recommendation using concept maps	Education
[27]	PCA, K-means	Uses PCA for dimensionality reduction and K-Means clustering to improve personalized product recommendations.	E-commerce
[3]	PCA	Uses PCA for feature extraction and a probabilistic approach to recommend visually similar products	E-commerce
[67]	XGBoost	Models historical financial patterns to predict stock price movements	Stock Market
[340]	XGBoost	Uses ensemble boosting to model complex user-item interactions and improve recommendation accuracy.	E-commerce
[359]	XGBoost	Combines multiple base learners with a meta-model to improve accuracy and robustness in purchase prediction	E-commerce.
[274]	XGBoost	Captures non-sequential user and contextual features to enhance ranking and prediction accuracy	Tourism
[317]	XGBoost	Models complex relationships among multiple aspects of tourist preferences to improve recommendation accuracy	Tourism
[55]	CatBoost	Processes categorical features and user–university interactions to enhance recommendation accuracy	Education
[8]	CatBoost	Predicting optimal duration of stay by modeling categorical and heterogeneous travel data	Travel

2.3 Deep Learning Approaches for Recommender Systems

Deep learning has revolutionized recommender systems, enhancing user experiences and driving sales across various online platforms [58]. In industry, its impact is profound: Netflix reports that 80% of watched movies come from recommendations [88], while YouTube states that 60% of video clicks originate from homepage suggestions [61]. Many leading companies leverage deep learning to refine recommendation quality, surpassing traditional methods [354]. Covington et al.[59] introduced a deep neural network-based recommendation algorithm for YouTube, while Cheng et al [53]. developed a Wide & Deep model for app recommendations on Google Play. Shumpei et al.[213] proposed an RNN-based news recommender for Yahoo News, demonstrating the effectiveness of deep learning [354]. This success is largely attributed to its ability to automatically capture increasingly complex nonlinear transformations and learn effective feature representations [92, 153]. As a subset of machine learning, deep learning involves training computer models to perform tasks by mimicking the operations of the human brain. Specifically, deep learning enables the training of complex models by using multi-layered artificial neural networks to represent and process data[24].

In recent years, deep learning has gained significant traction in various research domains like computer vision and natural language processing, not only for its remarkable performance but also for its ability to automatically learn complex feature representations from raw data. In the context of recommender systems, deep learning has proven particularly impactful, enabling personalized content delivery by capturing intricate user-item interactions, uncovering latent features, and effectively modeling sequential user behavior by using contextual, textual, and visual information, and integrate diverse data sources, overcoming many limitations of traditional methods [202, 354]. This category encompasses nine major neural network architectures commonly used in deep learning-based recommender systems: Artificial Neural Networks (ANN), Generative Adversarial Networks (GAN), Autoencoders (AE), Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Restricted Boltzmann Machines (RBM), Graph Neural Networks (GNN), Transformers and Attention mechanisms (including BERT), and Hybrid architectures.

- **Deep Neural Networks (DNN)**

  Deep neural networks [326] have demonstrated a strong ability to model complex relationships among users, items, and interactions in sequences, making them dominant in sequential recommendation systems (SRSs) in recent years. This approach can be broadly categorized into two types: SRSs built on basic deep neural networks and those that incorporate advanced models, enhancing their capacity to capture intricate sequential patterns and user behavior. Deep Neural Networks (DNNs) are widely used in various fields. In speech recognition, they enable systems like Google's Voice Assistant. Recommendation systems leverage DNNs for personalized content suggestions on platforms like Netflix and Amazon. These applications demonstrate the versatility and impact of DNNs in artificial intelligence [156].

2.3.0.1 Artificial Neural Networks (ANN)

Artificial Neural Networks (ANNs) are computational models inspired by the structure and function of the human brain. They consist of interconnected neurons organized in layers, with weighted connections that determine how information flows through the network. By applying activation functions and learning from data, ANNs can capture complex, non-linear relationships, making them highly suitable for recommendation tasks [253].

One major research direction in ANN-based recommender systems is the incorporation of contextual information. For instance, Liu et al. [169] developed a smart music playlist generator where time is treated as a critical contextual factor. Their system stores user profiles, including listening histories with timestamps, and extracts musical features from MIDI files to enhance personalization. Results showed that integrating temporal context improved playlist quality, suggesting that additional contextual factors such as mood could further enhance performance. Similarly, Biancalana et al. [33] proposed a context-aware movie recommendation system that combines ANN with collaborative filtering (CF). Their approach uses time intervals to group ratings, applies cross-correlation to capture temporal dynamics, and leverages ANN-based learning to identify household members. This integration of CF with contextual modeling significantly improved recommendation accuracy, highlighting the benefit of considering both user behavior and temporal factors. Krstić et al. [151] extended this line of research to digital TV program recommendations. They designed a single-layer feedforward ANN, combined with extreme learning machine (ELM) for faster training, to classify programs as "like" or "dislike" based on user preferences. The model reduces a 24-dimensional feature vector into three main viewing styles

(relaxing, informative, emotional) and incorporates contextual features such as day and time. Their results confirmed the importance of contextualization, showing higher accuracy compared to non-contextual baselines.

Meehan et al. [194] further demonstrated the versatility of ANNs by integrating them with fuzzy logic and Principal Component Analysis (PCA) in a tourism recommender system. Their model considered contextual dimensions like location, weather, and social sentiments. However, while promising, their work lacked a clear framework for integrating contextual features and preprocessing, indicating that data preparation remains a critical challenge in context-aware ANN models. Beyond purely context-aware models, researchers have explored hybrid strategies and domain-specific adaptations. Paradarami et al. [216] introduced a hybrid business recommendation system that combines content-based filtering with deep neural networks. Their model, tested with multiple activation functions, consistently outperformed traditional CF, showing that ANNs can effectively capture latent item-user interactions when combined with other recommendation techniques. In the tourism domain, Bahramian et al. [25] addressed the cold-start problem by combining Multi-Layer Perceptrons (MLP) with case-based reasoning. Their system generates initial tour recommendations via ANN and then refines them based on user feedback. Evaluation with survey data from Tehran confirmed that the hybrid design achieved better accuracy than standard CF approaches.

2.3.0.2 Convolutional Neural Networks (CNN)

Convolutional Neural Networks (CNNs) are highly effective for processing unstructured multimedia data through convolution and pooling operations. In recommendation systems, CNNs are primarily used for extracting rich, high-level features from diverse data sources. They excel in learning feature representations from inputs such as images, text, audio, and video. Specifically, CNNs are widely employed for image feature extraction, enabling systems to better understand visual content and enhance recommendation accuracy [354]. CNN-based recommendation algorithms enhance personalization by effectively analyzing users' attributes, item features, and rating data. By capturing both local and global patterns in the input, CNNs can uncover complex feature interactions, enabling more accurate and relevant item recommendations tailored to user preferences [60].

In 2016, Kim et al. [143] introduced a CNN-based matrix factorization model that leverages convolutional layers to extract semantic features from domain-related documents and contextual attributes. These CNN-derived representations were integrated with user and item latent factors to better capture hidden patterns and mitigate data sparsity. Experiments on MovieLens and Amazon datasets showed CNN-enhanced MF outperforming baseline methods by 3%, highlighting CNN's effectiveness in document context-aware recommendations.

Yang et al. [342] proposed a time-aware convolutional neural network (CNN) based personalized recommender system TC-PR leverages Convolutional Neural Networks (CNNs) to capture temporal dynamics in user-item interactions. CNNs extract sequential and contextual features from time-aware data, enhancing the modeling of evolving user preferences. This approach improves personalization by aligning recommendations with users' temporal behavior patterns. Safavi and Jalali [255, 256] proposed CNN-based POI recommendation model that incorporate friendship-aware features to improve personalization. RecPOID [255], emphasizes capturing spatial-temporal patterns and contextual dependencies from user check-ins, while DeePOF [256]

extends this by integrating deeper user–POI interaction learning in location-based social networks. Together, these works highlight the role of CNNs and social influence in enhancing POI recommendation accuracy.

Fudholi et al.[77] proposed a system applies Convolutional Neural Networks (CNNs) to model complex patterns in user-tourist behavior and contextual data. CNNs are used to extract high-level features from user interactions, enabling accurate representation of preferences.

2.3.0.3 Recurrent Neural Networks (RNN)

Recurrent Neural Networks (RNNs) are powerful models for review-based recommender systems, as they excel at processing sequential information. By modeling the sentiment flow and temporal progression within user reviews, RNNs provide deeper insights into user preferences and item characteristics [298]. They are particularly effective at capturing complex temporal dependencies and contextual relationships in sequential data. This ability allows RNNs to generate more accurate and personalized recommendations [108]. Overall, RNNs enhance recommendation quality by leveraging the rich sequential patterns embedded in textual feedback.

A context-aware recommendation system for sequential recommendations is proposed in [241], leveraging RNNs to capture temporal context in user interactions. The model effectively accounts for sequential patterns, enhancing the accuracy of recommendations. [348] proposed a dynamic recurrent model (DREAM) for next-basket recommendation by leveraging sequential user transaction data. RNNs are employed to capture temporal dependencies and evolving user purchase behaviors. By modeling sequential patterns, RNNs improve the accuracy of predicting users' future baskets. Similarly, [108, 298] introduced RNNs for session-based recommendation to model user interactions within a session. RNNs effectively capture sequential patterns and short-term dependencies in user clickstreams. By learning from session dynamics, RNNs improve recommendation accuracy without requiring long-term user histories.

RNNs model sequential data but face challenges with long-term dependencies, which LSTMs overcome using memory cells and multiple gates, while GRUs offer a simpler, faster alternative with similar effectiveness. Together, these architectures enhance RNNs by improving the modeling of temporal dependencies in complex sequence data [47, 338].

2.3.0.4 Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) networks [112] are specialized RNNs designed to capture long-term dependencies in sequential data using memory cells and gating mechanisms. Unlike traditional RNNs, LSTMs address the vanishing gradient problem [82], enabling the effective modeling of long-range patterns. Each memory cell maintains a cell state and a hidden state, regulated by input, forget, and output gates that control information flow. In recommender systems, LSTMs excel at modeling dynamic user behaviors over time, such as evolving preferences or session-based interactions. For instance, LSTMs can predict the next item a user might interact with based on previous actions, improving recommendation accuracy. Their ability to handle sequential, contextual information makes them ideal for personalized, time-sensitive suggestions. LSTM networks are widely used in applications like movie, e-commerce, and music recommendations, where user history influences future choices [202].

RNNs are increasingly popular in recommender systems for capturing sequential user behavior, but they struggle with modeling time intervals. To address this, Time-LSTM, a variant of

LSTM with time gates, was introduced by Zhu et al. [365] to better capture both short- and long-term user interests. Experiments on two real-world datasets demonstrate that Time-LSTM outperforms traditional methods in recommendation performance. In 2020, Sun et al. [295] presented a Long- and Short-Term Preference Modeling (LSTPM) approach addresses the challenge of capturing dynamic user preferences over time. By distinguishing between short-term and long-term user behaviors, the model can provide more accurate and personalized recommendations. This innovative method has the potential to significantly improve the effectiveness of Point-of-Interest recommendation systems across various applications. In 2023, Noorian et al. [209] introduced a Neural Network-LSTM-based POI recommendation system that personalizes sequential trip recommendations using BERT and deep learning. The approach calculates user similarity based on opinions, preferences, and multifaceted context while leveraging social media posts, feedback, and demographic data to address the cold start issue. Additionally, user reviews enhance collaborative filtering recommendations.

2.3.0.5 Transformers and Attention Mechanisms

In 2017, transformers emerged as a powerful deep learning model, introducing a new direction for recommender systems by enabling efficient handling of large-scale data and assigning dynamic weights to inputs. Unlike traditional sequential models, transformers allow parallel processing, which accelerates training and enhances scalability and performance in recommendation tasks [229]. Originally designed for natural language processing, transformers have demonstrated exceptional potential in recommendation systems due to their ability to model sequential data, capture long-range dependencies, and provide a more holistic understanding of user behavior over time through their self-attention mechanism [257]. The attention mechanism not only strengthens the performance of transformers but also addresses the interpretability challenges often associated with deep learning models. By assigning attention weights, it highlights the most informative features of items, identifies representative content, and offers more explainable and transparent recommendations. Its integration into architectures such as RNNs and CNNs further enhances sequential memory and emphasizes critical input regions, making attention-based modeling a promising and impactful direction for future recommender system research.

In 2014, Bahdanau et al. [24] pioneered the use of self-attention to identify relevant parts of an input sequence for a given target item, revolutionizing sequence-to-sequence models. Building on this foundation, Li et al. [159] introduced the Neural Attentive Recommendation Machine (NARM) in 2017, a neural network framework that leverages a hybrid encoder with self-attention to model both user behavior and session intent. NARM computes recommendation scores through a bi-linear matching scheme based on a unified session representation.

Subsequent advancements further refined self-attention for recommendation tasks. In 2020, Li et al. [160] proposed TiSASRec, which incorporates time interval self-attention to capture temporal patterns in user interactions, thereby enhancing preference inference. Similarly, Xu et al. [339] introduced a multilayer self-attention network in 2021 that integrates both long- and short-term user preferences, effectively capturing complex behavioral patterns in sequential recommendation. In 2022, Liu et al. [168] extended this line of research by presenting a model that not only integrates users' long- and short-term preferences but also captures item relationships, leveraging self-attention to model short-term interests while preserving contextual item relationships to improve embeddings and future behavior prediction.

Parallel to these developments, BERT-based models emerged as a powerful paradigm for recommendation. BERT's bidirectional architecture enables it to capture both preceding and succeeding contexts, providing a richer understanding of sequences and thereby generating highly accurate and personalized recommendations [68]. Unlike left-to-right unidirectional models that impose strict order constraints, BERT-based approaches allow more expressive hidden representations. For instance, in 2019, Sun et al. [294] introduced BERT4Rec, which employs deep bidirectional self-attention with a Cloze objective to predict masked items using both left and right context. This method achieved state-of-the-art performance across four benchmark datasets, though it faced challenges with large item vocabularies and suboptimal Top-K recommendations, leading researchers to explore generative models for greater diversity, coverage, and coherence.

Building on this foundation, Qiu et al. [237] proposed U-BERT in 2021, a pretraining and fine-tuning approach designed to enhance recommendation performance across domains. U-BERT effectively models complex user behaviors in content-rich domains during pretraining and adapts to content-scarce environments during fine-tuning. By integrating an item encoder and a review co-matching layer, it improves item representations and semantic interactions, achieving superior performance on six benchmark datasets. Further innovations came in 2022, when Zhao Qihang [356] introduced RESETBERT4Rec, a model that incorporates a rearrange sequence prediction task into the BERT pre-training framework while embedding diverse temporal information. Evaluations on public and e-commerce datasets demonstrated that RESETBERT4Rec consistently outperforms prior baselines. Most recently, Moon et al. [200] in 2024 proposed a BERT-based recommendation system tailored for education, which analyzes learners' profiles and past enrollments to generate personalized course suggestions. Tested on 3,678 Udemy courses spanning all proficiency levels, the model showcased strong performance and usability, highlighting the effectiveness of BERT in domain-specific sequential recommendation.

2.3.0.6 Autoencoders (AE)

Autoencoders (AEs) are unsupervised neural models designed to reconstruct input data through an encoding–decoding process, where the bottleneck layer captures compact latent feature representations. Conceptually, AEs can be regarded as a variant of multilayer perceptrons, with the primary objective of minimizing reconstruction error. Over time, several extensions—such as denoising autoencoders, sparse autoencoders, stacked autoencoders, and variational autoencoders—have been developed to improve robustness, generalization, and representational power.

Within recommender systems, AEs are widely applied in two main ways: (1) learning compact latent features for users and items, and (2) reconstructing the user–item interaction matrix to predict missing values. A representative model in this direction is AutoRec [268], which feeds either user-based or item-based rating vectors into an autoencoder and minimizes mean squared error for rating prediction. While AutoRec achieves strong performance, it suffers from limitations such as handling non-integer ratings and exacerbating sparsity when operating on partial vectors. To better accommodate implicit feedback, Strub et al. [289] proposed a collaborative filtering approach based on Stacked Denoising Autoencoders (SDAE), which introduces Gaussian noise into user preference vectors to learn robust representations. The model further employs negative sampling to reduce computational cost while preserving ranking quality. Overall, such autoencoder-based models demonstrate both the scalability and flexibility of neural architectures in collaborative filtering, effectively supporting rating prediction and ranking tasks. More recently, autoencoder-based methods have also been extended to sequential recommendation. For example, Liu et al. [172] introduced AutoSeqRec, an incremental model that combines autoencoders with a shared encoder and three decoders to jointly capture long- and short-term

user preferences. While collaborative filtering mechanisms are used to model long-term behaviors, item transition matrices are employed to track short-term interests within sessions. By integrating these components, AutoSeqRec provides a comprehensive solution to sequential recommendation, bridging static preference modeling with dynamic user behavior patterns.

2.3.0.7 Restricted Boltzmann Machine (RBM)

Restricted Boltzmann Machines (RBMs) are two-layer stochastic neural networks composed of a visible layer for input data and a hidden layer for feature extraction [109, 110]. Unlike traditional Boltzmann Machines, RBMs eliminate intra-layer connections, which significantly improves learning efficiency. The model defines a joint probability distribution over visible and hidden units, and parameters are optimized using maximum likelihood estimation. To make training more practical, Hinton [109] introduced Contrastive Divergence (CD), a fast approximation method that accelerates parameter updates while maintaining effectiveness.

RBMs can be stacked to form Deep Belief Networks (DBNs) through layer-wise training, enabling deeper architectures to learn richer and more hierarchical feature representations. In the context of recommender systems, Salakhutdinov et al. [258] proposed an RBM-based model where user ratings are represented as one-hot vectors to match the binary nature of visible units. Each user is modeled with an RBM containing softmax visible units for rated items, while weights and biases are shared across users to ensure consistent learning. This design allows RBMs to capture collaborative patterns effectively from rating data.

Building on this foundation, Liu et al. [174] extended RBM-based recommendation by incorporating Conditional RBMs (CRBMs), which leverage implicit feedback to enhance predictive accuracy. In this framework, activation probabilities for visible and hidden units are computed using the softmax and sigmoid functions, respectively, enabling the model to represent complex user–item interactions. Despite each RBM being trained on a single case, the shared parameters across users who rate the same items ensure that collaborative knowledge is efficiently propagated. These innovations established RBMs as an early yet powerful neural framework for collaborative filtering, offering strong performance in modeling user preferences, though challenges remain with scalability and handling non-binary ratings.

2.3.0.8 Generative Adversarial Network (GAN)

Generative Adversarial Networks (GANs) consist of two neural networks, a generator and a discriminator, trained in a minimax game where the generator tries to produce realistic data while the discriminator attempts to distinguish real from generated data. In recent years, GANs have attracted significant attention due to their strong ability to model complex real-world data distributions. This capacity has been effectively leveraged in the recommendation domain to mitigate the limitations of RSs. Broadly, two lines of research have emerged. First, to address data noise, adversarial perturbations and adversarial sampling-based training have been employed to improve model robustness. Second, to tackle data sparsity, data augmentation strategies have been developed, using GANs to capture the distribution of real data under the minimax framework, thereby enriching sparse datasets and enhancing recommendation performance. In the context of RSs, IRGAN [323] was one of the first systems to apply this concept, combining generative and discriminative approaches for information retrieval. The generative model learns to select items that resemble true relevant items, while the discriminative model aims to separate these generated items from actual user preferences. This adversarial training framework

refines both models iteratively, improving recommendation quality. In CF, this can be adapted by defining a scoring function for user preferences, typically using MF, where the user's interest in an item is represented as the dot product of their latent vectors. Despite their impressive performance, GANs remain theoretically challenging, with open questions about their training stability and generalization ability. Zhou et al. [360] proposed a Adversarial Point-of-Interest Recommendation (APOIR), applies GANs to improve POI recommendation by addressing data sparsity and noise. The generator models user check-in distributions to produce realistic candidate POIs, while the discriminator distinguishes real from generated interactions, enhancing robustness. Experimental results show that the GAN-based framework outperforms traditional methods in recommendation accuracy and reliability. In addition, Liu et al. [173] proposed a geographical information-based adversarial learning model (Geo-ALM) that integrates geographical information with GANs to improve POI recommendations. In this model, the generator produces unvisited POIs that closely align with user preferences, while the discriminator learns to distinguish between visited and unvisited POIs as accurately as possible. The effectiveness of Geo-ALM was validated on two public datasets, Foursquare and Gowalla, where it demonstrated superior performance compared to baseline methods.

2.3.0.9 Graph Neural Networks (GNN)

Graph Neural Networks (GNNs) have recently gained wide adoption in RSs due to their strong ability in graph representation learning [325]. Since most recommendation data inherently forms graphs (e.g., user–item interactions as bipartite graphs)[30, 347], GNNs provide a natural modeling framework. They enable unified representation of diverse information sources, including user–item relations, social networks, and knowledge graphs. Unlike traditional methods that capture collaborative signals implicitly, GNNs explicitly encode graph topology, enhancing user and item embeddings.

This allows modeling not only direct interactions but also higher-order multi-hop relationships, which significantly improve recommendation accuracy. Early approaches relied on graph embedding methods, while modern GNN-based models leverage message-passing to aggregate neighborhood information. They have been successfully applied across various recommendation tasks, including session-based, POI [337], multimedia, and group recommendation [327]. Industrial-scale systems, such as Pinterest's PinSage, demonstrate their scalability and effectiveness in real-world settings [74, 228, 347]. Li et al. [163] proposed a system that leverages Graph Neural Networks (GNNs) to capture collaborative signals among users and POIs. It transforms sequential check-in data into graph structures through iterative Seq2Graph augmentation, enabling richer relational modeling. Experimental results demonstrate that the GNN-based framework significantly improves next POI recommendation accuracy compared to sequential baselines. Howover, [344] introduced a system that integrates GNNs to capture complex user–attraction relationships beyond traditional similarity measures. GNNs model higher-order connectivity in the user–item interaction graph, enabling richer embeddings for personalized recommendations. This enhances the system's ability to recommend tourist attractions by leveraging both direct and indirect collaborative signals.

Table 2.2 provides a comprehensive summary of research studies on recommender systems utilizing deep learning techniques.

TABLE 2.2: Summary of Deep Learning-Based Approaches in Recommender System Research

Ref	Algorithm / Method	Function	Application Area
[169]	ANN	Generates personalized music playlists using MIDI features and timestamped listening history based on time of day	Music
[116]	ANN	Develops a utility-based system using Radial Basis Function Networks in e-commerce RS.	E-commerce
[33]	ANN	Enhances collaborative filtering with time-aware context and majority voting, using cross-correlation to capture temporal patterns.	Movie
[151]	ANN	Classifies TV preferences using time and weekday context, reducing inputs to three main styles.	Digital TV
[194]	ANN, PCA	Proposes a tourism recommender system using time, location, weather, and sentiment data but lacks detail on context preprocessing and integration.	Tourism
[216]	ANN	Use of ANN with content-based filtering to improve accuracy	Business
[25]	ANN	Tour recommendation integrating case-based reasoning	Tourism
[143]	CNN	Integrates semantic document and context features with latent factors to address data sparsity	Movie, E-commerce
[342]	CNN	Captures temporal dynamics and sequential features from user-item interactions	Movie
[255], [256]	CNN	Captures spatial-temporal and social features for better representation	POI
[77]	CNN	Learns high-level user and context features for accurate representation	Tourism
[241]	RNN	Capture sequential dependencies and context-aware patterns in user interactions	E-commerce
[348]	RNN	Models sequential dependencies in purchase histories to capture short- and long-term preferences for accurate next-basket recommendations	E-commerce
[108], [298]	RNN	Capture short-term user preferences through session behaviors like clicks and purchases.	E-commerce
[365]	LSTM	Captures temporal dynamics and long-term user behaviors to provide accurate time-sensitive recommendations.	Music, Academic paper
[295]	LSTM	Distinguishes long- and short-term user preferences for more accurate POI recommendations.	POI
[209]	BERT, LSTM	Sequential POI recommendations using user similarity, social media, and demographic context.	Tourism, POI
[159]	Self-Attention	Session-based recommendation using self-attention and bi-linear scoring.	E-commerce

Ref	Algorithm / Method	Function	Application Area
[160]	Self-Attention	Uses time-interval–aware self-attention to model sequential and temporal dynamics, improving recommendation accuracy.	Multimedia
[339]	Self-Attention	Employs self-attention to capture global and local user preferences, improving next-item prediction.	Multimedia
[168]	Self-Attention	Models user preferences and contextual dependencies to enhance personalized tourism recommendations	Tourism
[68]	BERT	capture richer contextual semantics from user behavior sequences for improved recommendations	E-commerce
[294]	BERT	Employs bidirectional self-attention to model user–item interaction sequences and improve next-item prediction	MultiMedia
[237]	BERT	To improve recommendation performance on one domain by leveraging the information from other domains.	Businesses
[356]	BERT	Integrates sequence rearrangement and time embeddings for better temporal modeling.	E-commerce
[200]	BERT	Uses learner profiles and enrollments for personalized course recommendations	E-learning
[268]	Autoencoder	RUses an encoder–decoder framework to learn latent features and predict missing user–item ratings	Movie
[289]	Autoencoder	Adds Gaussian noise and uses negative sampling to learn robust user preference representations efficiently	Movie
[172]	Autoencoder	Combines collaborative filtering and item transitions to model long- and short-term user preferences.	Movie
[258]	RBM	Learns latent features to model user–item interactions and capture nonlinear preference dependencies	Movie
[174]	RBM	Captures implicit feedback and complex user-item interactions using shared weights across users, with softmax and sigmoid activations.	Movie
[323]	GAN	Combines generative and discriminative models via adversarial training to learn latent representations for reconstructing relevance signals.	documents
[173]	GAN	Integrates geographical data with GANs to recommend unvisited POIs matching user preferences.	POI
[360]	GAN	Uses generator–discriminator training to tackle sparsity and noise, enhancing robustness and recommendation accuracy.	POI
[163]	GNN	Transforms sequential check-ins into graph structures to capture collaborative signals.	POI
[344]	GNN	Capture higher-order user–item connectivity and generate richer embeddings	Tourism

2.4 Multi-Criteria Decision Making (MCDM) Approaches in Recommendation Systems

Recommender systems play a vital role in helping users navigate information overload by suggesting relevant items across diverse domains, ranging from books and movies to complex decision-support tools. These systems rely on modeling user preferences and item attributes, often incorporating multiple criteria to enhance personalization and recommendation quality. In opinion-based recommendations, considering multiple factors is essential to improve user satisfaction, which has led researchers to propose the integration of Multi-Criteria Decision-Making (MCDM) techniques[23, 185]. MCDM methods are particularly valuable because they allow the inclusion of both scientific and subjective aspects into decision-making, ensuring transparency and systematic evaluation while accommodating non-quantitative factors [351]. By employing structured models or decision matrices, these methods provide a consistent basis for discussion, especially in situations where conflicts arise among decision-makers or where multiple criteria complicate the problem [214, 264]. Unlike traditional approaches that often aim for a single optimal solution, MCDM acknowledges that no universally best choice exists instead, it seeks to identify the most suitable alternative, select a subset of favorable options, or classify solutions into preference sets, including efficient or non-dominated outcomes[221]. This structured approach enables balancing trade-offs, enhancing diversity, and generating explainable recommendations, thereby fostering greater user trust. Furthermore, MCDM-based recommender systems are highly adaptable across domains, offering flexibility to integrate evolving user preferences and dynamic decision contexts. Their ability to provide personalized, transparent, and well-structured recommendations highlights their growing importance in modern recommendation research. Figure 2.7 presents an overview of MCDA methods and their main categories.
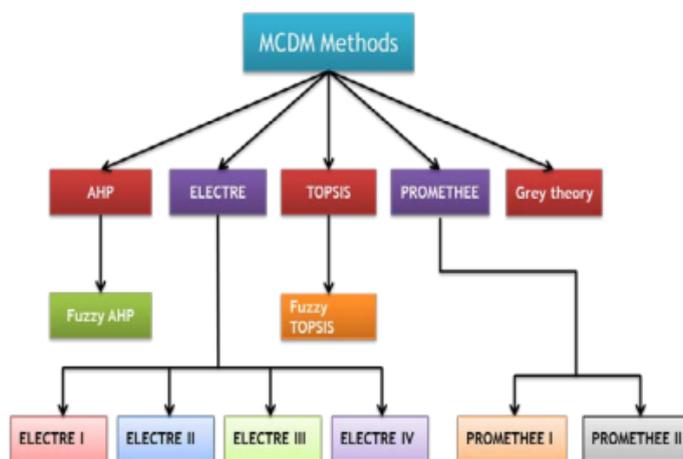
FIGURE 2.7: Hierarchical Classification of MCDM Methods. [221].

2.4.1 Importance of Multi-Criteria Decision-making (MCDM) in recommendations

Classical recommender system techniques rely on single-criterion evaluation, where users provide one overall rating per item. However, in many domains such as restaurants, evaluations naturally involve multiple aspects like food, service, and ambiance, highlighting the need for MCDM-based recommender systems. By considering multiple factors, MCDM enhances recommendation

accuracy and personalization [242]. These methods enable pairwise comparisons and express preferences through structured criteria, supporting ranking, selection, and classification tasks [4]. The objective is to build systems that ensure high accuracy, transparency, and ease of application while optimizing product rankings. As a result, MCDM-based recommendations become more relevant, structured, and user-centric, ultimately improving decision-making and user satisfaction.

2.4.2 Key MCDM Methods

In recommender systems, the decision object is an item i belonging to the set of all candidate items, often referred to as alternatives or actions in related literature [4]. To formalize decision-making, Roy [250] introduces the concept of decision "problematics," identifying four types:

- **Choice**: Selecting the most suitable alternative(s) from all candidates.

- **Sorting**: Classifying alternatives into predefined categories.

- **Ranking**: Ordering all alternatives from best to worst.

- **Description** : Evaluating each alternative based on multiple criteria.

These decision problematics are addressed in recommendation tasks through MCDM methods, which help enhance decision-making by considering multiple criteria. Among these methods are the following:

2.4.2.1 AHP (Analytic Hierarchy Process)

The **Analytic Hierarchy Process (AHP)**, introduced by Saaty (1980) [254], is a widely used MCDM method that supports personalized recommendations by structuring decision problems hierarchically and ranking alternatives through pairwise comparisons of criteria and options [314]. In recommender systems, AHP integrates both quantitative (e.g., ratings, usage metrics) and qualitative (e.g., user preferences, contextual factors) judgments to generate prioritized suggestions. Extensions like Fuzzy AHP (FAHP) further enhance its adaptability by handling uncertainty and vagueness in user preferences [87], leading to more accurate and user-centric recommendations.

Given a comparison matrix $A = [a_{ij}]$, the **priority vector** w is obtained as the principal eigenvector:

$$Aw = \lambda_{\max} w, \quad \sum_{i=1}^{n} w_i = 1 \tag{2.4}$$

Consistency is verified through the **Consistency Index (CI)** and **Consistency Ratio (CR)**:

$$CI = \frac{\lambda_{\max} - n}{n - 1}, \quad CR = \frac{CI}{RI} \tag{2.5}$$

where RI is the Random Index. Judgments are considered consistent if $CR < 0.1$ [37].

The Analytic Hierarchy Process (AHP) ranks and prioritizes alternatives through pairwise comparisons in a hierarchical structure. Its extensions address classical limitations: **AHPSort** supports classification into predefined categories, **ANP** captures interdependencies among criteria, **FAHP** integrates fuzzy logic to handle uncertainty, and hybrid models combine AHP with other MCDM methods to improve decision accuracy and applicability [252].

Park et al. [217] developed a restaurant recommendation system for group users in a mobile environment. It consists of four steps: context-log collection, individual preference modeling using a Bayesian network, and preference integration via AHP for multi-criteria decision-making. Quan et al. [238] proposed a hybrid recommender system that integrates the Analytic Hierarchy Process (AHP) with Bayesian Networks for Smart TV applications, where AHP is employed to evaluate and weight contextual factors such as user preferences, content type, and situational context. By combining these weighted criteria with Bayesian inference, the system generates personalized and context-aware recommendations, thereby enhancing user satisfaction. Similarly, Prasetyaningrum et al. [233] introduced a recommendation system that integrates AHP with sentiment analysis, where AHP structures and weighs multiple criteria to ensure that user preferences and priorities are systematically incorporated into decision-making. Extending the role of AHP in educational domains, Wongvilaisakul et al. [334] developed a graduate admission recommender system using both AHP and Fuzzy AHP, enabling dynamic evaluation of multiple admission criteria by incorporating both quantitative and qualitative factors. Toledo et al. [307] proposed a food recommender system that integrates nutritional information with user preferences to suggest healthier meal options. The AHPSort method is used to weigh different nutritional attributes such as calories, proteins, and fats against user taste preferences. This structured decision-making process ensures personalized recommendations that balance health requirements with individual dietary choices.

2.4.2.2 UTA (UTilités Additives)

The UTA (UTilités Additives) method [281] is a preference disaggregation approach that infers an additive utility function from a user's ranking of alternatives, enabling recommender systems to model individual preferences and generate personalized item suggestions based on multiple criteria. The global utility of an alternative a is defined as:

$$U(a) = \sum_{i=1}^{n} p_i \, u_i(g_i(a)), \quad \sum_{i=1}^{n} p_i = 1 \tag{2.6}$$

where $u_i(g_i)$ are marginal utility functions and p_i are criterion weights. The model preserves monotonicity:

$$U(a) > U(b) \iff a \succ b, \qquad U(a) = U(b) \iff a \sim b \tag{2.7}$$

Each criterion g_i is discretized and marginal utilities are estimated by linear interpolation. Consistency with the ranking requires:

$$U(a_k) - U(a_{k+1}) \geq \delta \ \text{ if } a_k \succ a_{k+1}, \quad U(a_k) - U(a_{k+1}) = 0 \ \text{ if } a_k \sim a_{k+1}. \tag{2.8}$$

The marginal functions are obtained by solving the linear program:

$$\min \ F = \sum_{a \in A_R} \sigma(a) \tag{2.9}$$

subject to normalization, monotonicity, and ranking constraints. If $F^* = 0$, preferences are perfectly represented; otherwise deviations $\sigma(a)$ indicate inconsistency. Post-optimality analysis then explores admissible solutions to assess weight stability and criterion importance.

Lakiotaki et al. [155] proposed UTA-Rec, a recommender system based on the Utility Additive (UTA) multiple-criteria analysis, where overall utility is decomposed into additive criteria, enabling systematic aggregation of user preferences across multiple dimensions. Building on this approach, Lakiotaki et al. [154] introduced a multi-criteria user modeling method for recommender systems, which similarly decomposes overall user preferences into multiple criteria to allow structured evaluation and aggregation of items. Extending the application of UTA to the mobility domain, Amoretti et al. [20] proposed UTravel, a smart mobility recommender system that models user preferences across multiple travel criteria and aggregates them using additive utility functions to evaluate mobility options effectively.

2.4.2.3 Multi-Attribute Utility Theory (MAUT)

Multi-Attribute Utility Theory (MAUT) is a widely used MCDM method that evaluates alternatives based on multiple qualitative and quantitative criteria [95]. In recommender systems, MAUT computes an overall utility for each item by aggregating weighted utilities of individual attributes, balancing trade-offs among user preferences, ratings, and contextual factors [261, 300]:

$$U(i) = \sum_{j=1}^{d} w_j \cdot u_j(x_{ij}) \tag{2.10}$$

where w_j is the weight of criterion c_j, x_{ij} is the performance of item i on criterion c_j, and $u_j(\cdot)$ is the utility function for that criterion. The item with the highest $U(i)$ is recommended, ensuring personalized and accurate multi-criteria selection.

Huang et al. [116] investigated utility-based recommender systems for e-commerce, highlighting the role of Multi-Attribute Utility Theory (MAUT) in modeling user preferences by systematically eliciting and aggregating them across multiple attributes to support personalized decision-making. Extending this approach, Deng et al. [64] proposed a MAUT-based recommender system enhanced with a genetic algorithm, where implicit utility values are estimated from user behavior and attribute weightings are optimized through evolutionary search. In the educational domain, Maravanyika et al. [186] applied MAUT to select relevant attributes for recommender systems, evaluating multiple educational criteria and assigning utility scores to quantify the relative importance of each attribute.

2.4.2.4 TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution)

The TOPSIS method ranks items in recommender systems by evaluating their relative closeness to a positive ideal solution (PIS), representing the most preferred characteristics, and a negative ideal solution (NIS), representing the least preferred characteristics. For benefit criteria J_1 and cost criteria J_2, the ideal solutions are:

$$A^+ = \{\max x_{ij} \mid j \in J_1, \min x_{ij} \mid j \in J_2\}, \quad A^- = \{\min x_{ij} \mid j \in J_1, \max x_{ij} \mid j \in J_2\}. \quad (2.11)$$

The Euclidean distances from each alternative to the ideal solutions are:

$$D_i^+ = \sqrt{\sum_{j=1}^{n}(x_{ij} - A_j^+)^2}, \quad D_i^- = \sqrt{\sum_{j=1}^{n}(x_{ij} - A_j^-)^2}. \quad (2.12)$$

The relative closeness coefficient is then defined as:

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-}. \quad (2.13)$$

A higher C_i indicates a better alternative, making TOPSIS an effective method for multi-criteria ranking and selection in recommender systems [120].

Musrini et al. [203] employed the TOPSIS method to help buyers select the most suitable smartphone by ranking alternatives based on features and brand preferences, further validating the approach within a Decision Support System by comparing results with manual calculations. Similarly, Dewi et al. [66] applied TOPSIS to rank tourism destinations by evaluating criteria such as accessibility, facilities, and popularity, where the method calculates each option's relative closeness to the ideal and anti-ideal solutions to ensure structured and consistent recommendations. Extending its application to entertainment, Vali et al. [315] introduced TopMoviePicks, a personalized movie recommender system that uses TOPSIS to assess criteria such as genre, ratings, and user preferences, ranking movies by their closeness to the optimal choice and thereby enhancing personalization in recommendations.

2.4.2.5   ELECTRE (Elimination Et Choice Translating Reality)

ELECTRE is an MCDM method used in recommender systems to identify alternatives that provide the highest user satisfaction while minimizing conflicts among multiple criteria [349]. Its core concept is the outranking relation, which compares alternatives using concordance and discordance indices. For alternatives a and b:

$$C(a,b) = \frac{\sum_{j \in J^+} w_j}{\sum_{j=1}^{n} w_j}, \quad D(a,b) = \max_{j \in J^-} \frac{|x_{bj} - x_{aj}|}{\max_{k,l} |x_{kj} - x_{lj}|}, \quad (2.14)$$

where J^+ and J^- are criteria sets where a is at least as good or worse than b, respectively. Alternative a outranks b if:

$$C(a,b) \geq C^*, \quad D(a,b) \leq D^*, \quad (2.15)$$

with C^* and D^* as predefined thresholds. ELECTRE has several variants (I–IV, TRI) adapted to different decision problem types.

Lian et al. [164] proposed a system that applies a modified ELECTRE method to develop an agricultural product recommendation service for mobile devices, where concordance and discordance measures are used to balance conflicting criteria and provide farmers with efficient, accurate product selection. Extending ELECTRE to the education domain, Marlinda et al. [187] introduced a program recommender system that assists students in selecting suitable multi-study programs by establishing outranking relations among alternatives and filtering out dominated options, thereby aligning recommendations with both student preferences and objective academic requirements. More recently, Pramudya et al. [232] applied ELECTRE to tourism by designing a recommender system for destinations in Banyumas Regency, where multiple criteria such as location, facilities, and user preferences are evaluated within the concordance–discordance framework. This system, integrated with an API service and interactive mapping, enhances usability and accessibility for tourists while effectively resolving conflicting criteria.

2.4.2.6 PROMETHEE (Preference Ranking Organization Method for Enrichment Evaluations)

PROMETHEE is an MCDM method widely used in recommender systems to rank alternatives based on multiple criteria [35]. For each criterion j, a preference function $P_j(a, b)$ evaluates the difference between alternatives A and B:

$$d_j = f(A_j) - f(B_j) \tag{2.16}$$

The multicriteria preference index aggregates these pairwise comparisons:

$$\Pi(a, b) = \frac{\sum_{j=1}^{J} w_j P_j(a, b)}{\sum_{j=1}^{J} w_j}, \tag{2.17}$$

where w_j is the weight of criterion j. Outranking flows quantify dominance:

$$\phi^+(a) = \sum_{b \in A} \Pi(a, b), \quad \phi^-(a) = \sum_{b \in A} \Pi(b, a), \quad \phi(a) = \phi^+(a) - \phi^-(a). \tag{2.18}$$

The alternative with the highest net flow $\phi(a)$ is recommended:

$$a \succ b \iff \phi(a) > \phi(b), \quad a \sim b \iff \phi(a) = \phi(b). \tag{2.19}$$

Variants of PROMETHEE Several variations of the PROMETHEE method exist:

- **PROMETHEE I:** Provides a partial ranking, allowing for possible incomparabilities.

- **PROMETHEE II:** Produces a complete ranking of alternatives.

- **PROMETHEE V:** Extends PROMETHEE II by incorporating constraints for the selection of multiple options.

Similarly, in 2019, Zuraidah [367] applied the PROMETHEE method in a traveler recommendation system, analyzing tourist preferences for Bali attractions. Surveys and interviews considered factors like cost, security, natural beauty, facilities, and infrastructure to enhance decision support.

Pelitli et al. [227] proposed a web-based application to determine individual food preferences using the PROMETHEE method. Multiple nutritional and sensory criteria such as taste, appearance, and nutritional value are evaluated to rank food alternatives. PROMETHEE's pairwise comparison and preference functions provide a transparent and systematic approach for personalized food recommendations.

Setiawan et al. [272] introduced a culinary business recommendation application employing the PROMETHEE-II method. The system evaluates multiple business criteria, such as location, price, and customer preferences, using preference functions to establish rankings. PROMETHEE-II ensures fair comparisons and delivers effective recommendations to guide culinary business decisions.

Table 2.3 provides an overview of MCDM approaches applied in recommender system research.

TABLE 2.3: Summary of MCDM-ML Based Approaches in Recommender System Research

Ref	Algorithm / Method	Function	Application Area
[217]	AHP	Uses Bayesian modeling and AHP to integrate individual preferences for group restaurant recommendations in mobile contexts.	Restaurant
[238]	AHP	Combines AHP-weighted contextual factors with Bayesian inference to deliver personalized Smart TV recommendations.	Smart TV
[307]	AHPsort	Integrates nutritional needs and user preferences using MCDA and optimization for meal planning.	Food
[233]	AHP	Combines AHP weighting with sentiment analysis to capture user opinions and improve recommendation accuracy.	Restaurant
[334]	AHP, Fuzzy AHP	Uses dynamic multi-criteria decision making to evaluate admission factors and improve fairness in graduate recommendations.	Education
[155]	UTA	Aggregates user preferences with multi-criteria analysis to rank items by utility for personalized recommendations.	Movie
[154]	UTA	Models and aggregates user preferences with additive utility functions to deliver personalized recommendations.	Movie
[20]	UTA	Profiles users on multiple travel criteria and applies additive utility functions to deliver personalized mobility recommendations.	Smart Mobility
[116]	MAUT	Develops a utility-based system using Radial Basis Function Networks in e-commerce RS.	E-commerce

Ref	Algorithm / Method	Function	Application Area
[64]	MAUT	Derives implicit utility from user behavior and optimizes attribute weights via genetic algorithms to enhance recommendation accuracy.	E-commerce
[186]	MAUT	Aggregates educational criteria with utility scores to provide personalized learner recommendations.	Education
[203]	TOPSIS	Ranks smartphones by features and user preferences, validated against manual selection results.	E-commerce
[66]	TOPSIS	Ranks tourism destinations based on closeness to ideal and anti-ideal solutions to match user preferences.	Tourism
[315]	TOPSIS	Ranks movies by measuring closeness to ideal and negative-ideal solutions for personalized recommendations.	Movie
[187]	ELECTRE	Uses concordance and discordance indices to establish outranking relations and eliminate dominated options.	Education
[164]	ELECTRE	Delivers mobile agricultural product recommendations using concordance and discordance measures to help farmers choose optimal products.	Agriculture
[232]	ELECTRE	Applied the ELECTRE method with API-based interactive mapping to recommend tourist destinations in Banyumas Regency.	Tourism
[367]	PROMETHEE	Traveler recommendations for Bali attractions based on factors such as cost, security, and beauty.	Travel
[227]	PROMETHEE	ses PROMETHEE to evaluate nutritional and sensory criteria and generate personalized food rankings.	Food
[272]	PROMETHEE-II	Applies PROMETHEE-II to assess key criteria and produce effective decision-support rankings.	Culinary Business

2.5   Comparative Analysis and Discussion

The comparative analysis of various recommender system approaches highlights the evolution of recommendation techniques, particularly Multi-Criteria Decision-Making (MCDM), Machine Learning (ML), and Deep Learning (DL) techniques. Each approach contributes distinct advantages while also presenting notable limitations, shaping the trajectory of recommendation research and applications.

MCDM methods, such as the Analytic Hierarchy Process (AHP), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), and Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE), provide a structured way to incorporate multiple user-centric criteria. Their strengths lie in transparency, interpretability, and explicit preference modeling. However, these methods are often constrained by scalability challenges when applied to large datasets, and they may struggle to adapt to dynamic or uncertain user preferences.

Machine Learning approaches, including Support Vector Machines (SVM), K-Nearest Neighbors (KNN), Random Forest, and gradient boosting techniques, offer efficiency in handling structured data while ensuring relatively fast computation and practical deployment. They are particularly effective for recommendation tasks requiring moderate complexity and robustness. Nonetheless, these methods often face challenges in capturing highly nonlinear user–item interactions and are prone to cold-start and data sparsity issues, which limit their performance in rapidly evolving recommendation environments.

Deep Learning-based models, such as CNNs, RNNs, LSTMs, and Transformer architectures, have significantly advanced the field by enabling automatic feature extraction and learning complex latent patterns. Their adaptability to heterogeneous data modalities—including text, images, and sequential interactions—makes them highly powerful for personalized and context-aware recommendations. Despite these strengths, DL models demand extensive computational resources, large-scale datasets, and often suffer from limited interpretability, which complicates their practical integration in real-world systems.

While MCDM, ML, and DL each bring valuable perspectives, their individual limitations underscore a critical research gap. Current trends point toward hybrid and context-aware recommender systems that strategically combine these paradigms: leveraging the transparency of MCDM, the efficiency and scalability of ML, and the representational power of DL. Such integrated frameworks hold the potential to achieve a balance between interpretability, predictive accuracy, and adaptability, ultimately leading to more robust and user-centric recommendation solutions

An overview of comparative studies and notable implementations across various domains underscores the complementary nature of these approaches:

Approach	Strengths	Limitations and Applications
ML	Interpretable, scalable, efficient with structured data	Cold-start problem, poor handling of unstructured data. Used in restaurant, tourism, and career recommendation [21, 217].
DL	Captures complex patterns and sequential data; effective with unstructured inputs	High resource demand, limited interpretability. Applied in music, tourism, and e-commerce [209, 321].
MCDM	Transparent, user-centric, incorporates multiple criteria	Less predictive power, scalability issues. Used for career guidance, travel planning [187, 203].
Hybrid (ML/DL + MCDM)	Combines predictive and decision-making strengths; better accuracy and user alignment	Complex integration, computation overhead. Seen in smart tourism and food recommendation systems [20, 307].

2.6 Conclusion

In conclusion, this chapter has explored the integration of Machine Learning, Deep Learning, and Multi-Criteria Decision-Making (MCDA) approaches in recommendation systems. Machine learning techniques, provide diverse methods for generating personalized recommendations based on user preferences and item characteristics. Deep learning methods, including autoencoders, neural networks, and transformers, enhance the ability to capture complex patterns and dynamic behaviors in user-item interactions. Additionally, MCDA methods introduce a structured approach to incorporating multiple criteria, improving the quality and relevance of recommendations. By combining these approaches, recommender systems can achieve higher accuracy, adaptability, and user satisfaction. As the field continues to evolve, the synergy between these methods will play a crucial role in advancing personalized recommendation technologies.

Part II

Proposed Recommender System

CHAPTER 3

A MULTI-CRITERIA FOOD AND RESTAURANT RECOMMENDATION SYSTEM

Chapter contents

3.1   Introduction

In this chapter, we propose SFRA, a multi-criteria recommendation system tailored to healthier and more personalized food choices. The rapid growth of online platforms has created an overload of dining options, leaving users struggling to identify meals that match their dietary needs and preferences. Conventional RSs often overlook health-related factors, focusing mainly on popularity or convenience. SFRA addresses this gap by incorporating nutritional balance, lifestyle goals, and contextual factors into the recommendation process. It builds on enriched user profiles that combine dietary requirements, taste preferences, and geographic location. To ensure accurate evaluation, SFRA applies AHP and TOPSIS for ranking restaurants and meals.

The system not only improves user satisfaction but also encourages healthier eating decisions. By merging personalization with health-awareness, SFRA contributes to combating issues like obesity and poor diet quality. Ultimately, it delivers benefits at both the individual and societal levels, promoting well-being through informed food choices. The remainder of the chapter is organized as follows. Section provides a detailed description of the proposed approach. Section 3.3 provides the experimental evaluation, along with the presentation and discussion of the results. Finally, Section 4.4 concludes the chapter by summarizing the key findings.

3.2   A Smart Food and Restaurant Advisor (SFRA)

This section presents a Smart Food and Restaurant Advisor (SFRA), which is a novel food and restaurant recommendation system. The latter is determined by a users' profile, which includes their location, dietary requirements, and preferences. User profiling (Point 3.2.1 below) and filtering and recommendation (Point 3.2.2 below) are its two primary procedures. Numerous user attributes, including demographics, physical characteristics, and restaurant preferences, are included in the used database. Together with a database of eateries and their recipe databases, which were used to categorize the cuisine, these qualities serve as the foundation for the filtering process.

Figure 3.1 summarizes the architecture of the proposed system and shows the main phases that are involved in its functioning. We present below a description of such architecture.
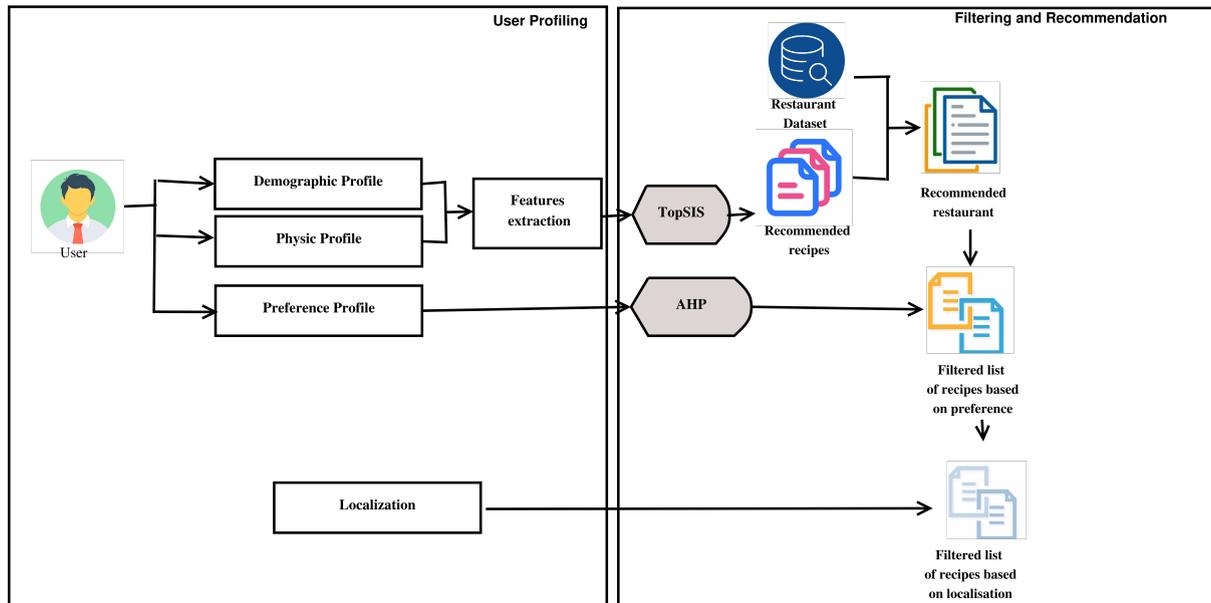
FIGURE 3.1: *The proposed system architecture.*

3.2.1   User Profiling

Our aim is to give a general yet accurate description of the user. To achieve this objective, we consider a number of characteristics, such as preferences, geographic location, and demographic and physical data. This thorough profile serves as the basis for the process of personal recommendations. Below, we offer a detailed explanation of this step's various components. Figure 3.2 illustrates the process of User Profiling.
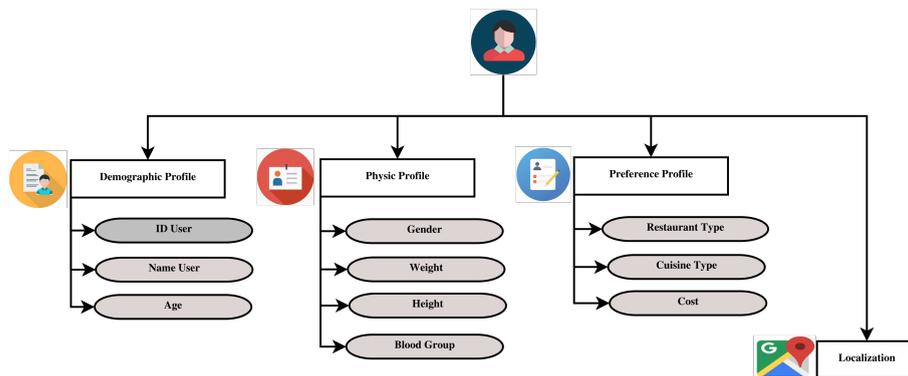
FIGURE 3.2: User profiling process

Generating User Profile:

User profiles are generated by collecting and analyzing relevant information, including demographic and physical attributes and activity level. The user profile consists of the following:

1. **Demographic Profile:** Basic information such as *user ID* and *age*. This profile acts as an initial user profile, addressing the *cold start problem* and enabling recommendations based on limited data.

2. **Physical Profile:** Attributes like *gender*, *weight*, and *height*. These metrics are used to develop a dietary needs profile, which is further refined using the *TOPSIS* multi-criteria decision-making method to select appropriate food options available in restaurants. Key Metrics: Using demographic (e.g., *Height* (in meters), *weight* (in kilograms), *age* (in years), *gender*, and *activity level*. The Harris-Benedict equation [181] is used to estimate the Basal Metabolic Rate (BMR), which, when multiplied by an activity factor, provides the approximate daily caloric intake to maintain the user's current weight. User activity levels categorized as *stable*, *slightly active*, *moderately active*, *very active*, and *extremely active*, the following metrics are computed:
Body Mass Index (BMI): Computed using Equation 3.1.

$$BMI = \frac{\text{weight (kg)}}{\text{height (m)}^2} \tag{3.1}$$

BMR (Male and Female): Estimated using Equations 3.2 and 3.3 for male and female respectively.

$$\text{BMR (male)} = 66 + (13.7 \cdot \text{weight (kg)}) + (5 \cdot \text{height (cm)}) - (6.8 \cdot \text{age}) \tag{3.2}$$

$$\text{BMR (female)} = 655 + (9.6 \cdot \text{weight (kg)}) + (1.8 \cdot \text{height (cm)}) - (4.7 \cdot \text{age}) \tag{3.3}$$

Total Daily Energy Expenditure (TDEE): Calculated using Equation 3.4.

$$TDEE = \text{BMR} \cdot \text{activity multiplier} \tag{3.4}$$

These metrics help assess the user's nutritional requirements, forming the basis for determining optimal proportions of *fat*, *protein*, and *carbohydrates* tailored to their needs.

- **BMI Category :** classification individuals into BMI categories based on their calculated Body Mass Index (BMI). The categories are defined as follows:

TABLE 3.1: BMI Category Classification

BMI Category	BMI Range (kg/m^2)
Underweight	Less than 18.5
Normal weight	18.5 – 24.9
Overweight	25 – 29.9
Obese	30 or greater

A recommended goal, based on the current BMI:

- The *Lose weight* if the BMI exceeds 24.9
- The *Gain weight* if the BMI is below 18.5
- The *Maintain weight* if the BMI is within the normal range

Offers practical guidance to support individuals in achieving and maintaining a healthy weight. Daily Caloric Needs: calculates the caloric intake required to meet specific weight goals over a given period (in days). Using a person's weight (in kilograms) and the desired goal (weight loss or gain), as follows :

- *Calories to lose weight:* By consuming fewer calories than burned daily

      – *Calories to gain weight:* By consuming more calories than burned daily

Helps users set realistic caloric targets aligned with their dietary objectives.

- **TDEE Goal:** adjusts the Total Daily Energy Expenditure (TDEE) based on a user's weight management goals. Using the TDEE, a specified goal (*lose, gain, or maintain weight*), and the daily caloric requirement, the function computes the adjusted TDEE as follows:

      – *Weight loss:* Subtract the daily caloric value from the TDEE.

      – *Weight gain:* Add the daily caloric value to the TDEE.

      – *Weight maintenance:* TDEE remains unchanged.

This ensures accurate caloric adjustments that align with the user's desired outcomes.

The relationship between activity level and calorie intake is shown in Table 3.2.

Lifestyle	Multiplier	Calorie Intake (approx.)
Sedentary	1.2	BMR · 1.2
Lightly Active	1.375	BMR · 1.375
Moderately Active	1.55	BMR · 1.55
Very Active	1.725	BMR · 1.725
Extra Active	1.9	BMR · 1.9

TABLE 3.2: Calorie intake based on Basal Metabolic Rate [181].

3. **Preference Profile:** User preferences (e.g., cost, ambiance, adress code) are assessed using the *AHP* multi-criteria method. This method identifies the most relevant criteria and ranks restaurants accordingly for personalized recommendations.

4. **Localization:** User location (latitude and longitude) is utilized to suggest nearby restaurants that match dietary and preference profiles, enabling accurate and tailored recommendations.

3.2.2 Filtering and recommendation

Filtering considers the user's nutritional requirements, preferences, and location. By utilizing a dataset of restaurants and recipes, the system organizes dishes and food establishments according to the user's specific nutritional requirements. For each category, the filter selects options that best align with the user profile. Our approach provides users with personalized recommendations tailored to their dietary needs. Specifically, our recommendations offer guidance on food and restaurants based on the user's nutritional requirements, preferences, and location.

- Recommended Food: The recommended items consist of food available on restaurant menus. These food items are categorized based on their nutritional components to align with users' daily dietary needs. The categories in this recommendation system include bread, main dishes, side dishes, world cuisines, desserts, breakfast and brunch, salads, soups, stews and chili, meat and poultry, drinks, appetizers and snacks, beans and lentils, restaurant foods, beverages, dairy and egg products, vegetables, fish, cereals, fast food, grains, seafood, fried potatoes, entrees, baked goods, and more.

- Recommended restaurant: The suggested restaurant has a variety of features. These characteristics include the kind of food that is served, the components that go into each dish, and the restaurant's location (as indicated by latitude and longitude). Additionally, it considers the distinctive qualities of every restaurant, like its cost, as well as other elements that suit customer preferences.

3.2.3 Localization Restaurant Recommendation Filtering Algorithm

Prior filtering methods are confined to make suggestions at the expense of users' dietary needs and preferences since they do not take into account the opinions of all users when making recommendations. Therefore, we wanted to provide details about the user's domain-specific. Combining various recommendation methods is thought to produce an algorithm that makes recommendations that are more precise and useful.

We proposed the Localization Restaurant Recommendation Filtering Algorithm (LRRFA) as part of the SFRA system. This algorithm integrates the TOPSIS method with the preference-based filtering algorithm. This combination allows the SFRA system to compare user preferences with restaurant features, enhancing the relevance of the recommendations. Additionally, by incorporating contextual data such as user location, the algorithm identifies restaurants close to the user's current location, offering a more personalized and convenient experience. Recommendations are based on dietary needs, preferences, and proximity, while also considering health conditions, such as diabetes, to suggest appropriate food options.

The recommendation process involves selecting top dishes in a preferred food category using the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). This method ranks alternatives based on their similarity to a positive ideal solution (PIS) and their dissimilarity to a negative ideal solution (NIS). A normalized decision matrix A is constructed, where the rows represent dishes, and the columns represent nutritional attributes. Mathematically, the PIS and NIS are computed based on the user's dietary needs. The TOPSIS score for each dish is determined using the Euclidean distance from the PIS and NIS. Dishes with the highest scores are selected for recommendation.

User preferences are analyzed using the Analytic Hierarchy Process (AHP), a multi-criteria decision-making technique. This process involves pairwise comparisons of criteria to evaluate their relative importance. A comparison matrix C is constructed, where C_{ij} represents the preference of criterion i over criterion j. The matrix is normalized to produce the priority vector w, which captures the weights of each criterion. This process results in a hierarchical tree that organizes the criteria and their relative weights.

Similarly, we applied AHP method to compare restaurants. The criteria considered include restaurant type, cuisine type, and cost. Each criterion has an associated comparison matrix and priority vector. Weights are assigned to these criteria based on their importance to the recommendation process. The comparison matrices are then integrated into a hierarchical structure, which enables an effective comparison of restaurant options.

We employed the TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) method, considering key factors such as Body Mass Index (BMI), Basal Metabolic Rate (BMR), and Total Daily Energy Expenditure (TDEE).

The evaluation process begins by identifying the criteria that define the decision problem. These criteria represent different nutritional aspects, including Fat, Carbohydrates, and Protein.

A. Decision Matrix Formation

The decision matrix X is constructed with m rows corresponding to alternative food options and n columns representing nutritional criteria, such as fat (F), carbohydrates (C), and protein (P) content. Each element x_{ij} in the matrix denotes the quantity of the jth nutrient $(j = 1, 2, 3)$ in the ith food option. The matrix is defined as follows:

$$X = \begin{bmatrix} x_{11} & x_{12} & x_{13} \\ x_{21} & x_{22} & x_{23} \\ \vdots & \vdots & \vdots \\ x_{m1} & x_{m2} & x_{m3} \end{bmatrix}$$

B. Normalization of Data

To standardize the data and ensure comparability across various criteria, normalization is applied to each element in the decision matrix. The normalized value for each element is calculated using the formula:

$$x_{ij}^* = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \tag{3.5}$$

This process ensures that all criteria are expressed on a comparable scale, eliminating differences arising from variations in units or magnitudes.

After normalization, each criterion's *ideal best* and *ideal worst* alternatives are determined. For a given criterion, the *ideal best* denotes the most desirable value, and the *ideal worst* denotes the lowest desirable value. When assessing the alternatives, these ideal solutions act as benchmarks:

$$A_j^+ = \max(x_{ij}) \quad \text{(ideal best)}$$
$$A_j^- = \min(x_{ij}) \quad \text{(ideal worst)}$$

C. Identification of Ideal Solutions

The user's dietary preferences and limitations are taken into consideration when determining the positive and negative optimum solutions (PIS and NIS). For example, low values indicate the PIS for fat (F^+) and NIS for protein (P^-) if the user wants to consume as much protein as possible and as little fat as possible.

$$\text{PIS: } (F^+, C^+, P^+) \quad \text{NIS: } (F^-, C^-, P^-)$$

D. Calcul of Distances

Both the D_i^+ and D_i^- Euclidean distances are calculated to measure how close each food option is to the ideal solutions. The following formulas are used to compute these distances:

$$D_i^+ = \sqrt{\sum_{j=1}^{n}(x_{ij}^* - p_j^*)^2} \tag{3.6}$$

$$D_i^- = \sqrt{\sum_{j=1}^{n}(x_{ij}^* - n_j^*)^2} \tag{3.7}$$

E. Evaluation of Relative Closeness

The following formula is used to calculate each food option's relative proximity (C_i) to the ideal solutions:

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-} \tag{3.8}$$

where D_i^+ and D_i^- represent the distances of the i-th option from the Positive Ideal Solution (PIS) and Negative Ideal Solution (NIS), respectively.

A higher C_i indicates greater suitability of the food option for the user's dietary needs.

F. Ranking of Food Options

The relative proximity scores of the food selections are used to rank them; higher scores indicate better alignment with the user's dietary preferences. Additional factors or user preferences may be taken into consideration for resolution in the event of ties.

$$\text{Ranking: } Food_1 > Food_2 > \cdots > Food_m$$

3.2.3.1 Analytic Hierarchy Process (AHP) for Restaurant Selection

The Analytic Hierarchy Process (AHP) is a decision-making framework developed by Thomas Saaty in the 1970s. This structured technique helps individuals or groups handle complex decisions by organizing them into a hierarchy of criteria and alternatives, followed by systematic evaluation and comparison of these elements based on their relative importance or preference [254].

A. Pairwise Comparison

The process begins by constructing a pairwise comparison matrix C for the criteria C_1, C_2, and C_3. Users provide judgments regarding the relative importance of each criterion. Let c_{ij}

represent the user's assessment of the importance of criterion i relative to criterion j. The matrix C is a square matrix where c_{ij} quantifies this relationship.

B. Pairwise Comparison Matrix

The pairwise comparison matrix C is defined as:

$$C = \begin{bmatrix} 1 & c_{12} & c_{13} \\ \frac{1}{c_{12}} & 1 & c_{23} \\ \frac{1}{c_{13}} & \frac{1}{c_{23}} & 1 \end{bmatrix}$$

The diagonal elements are always 1, as a criterion is equally important compared to itself. The elements above the diagonal (c_{ij}) represent the user's input, while the elements below $(\frac{1}{c_{ij}})$ are their reciprocals.

C. Eigenvalue Calculation

To determine the relative weights of the criteria, we calculate the principal eigenvector of the matrix C. Let w represent the eigenvector corresponding to the largest eigenvalue of C.

D. Normalization

The eigenvector w is normalized to ensure that its components sum to 1. The normalized eigenvector w' is obtained by dividing each element of w by the sum of all elements in w. This normalization ensures that the weights are proportional and interpretable as probabilities.

E. Aggregation of Weights for Restaurants

For each restaurant r, an aggregated score S_r is computed based on its attributes and the normalized weights w'. Let $A_r = [A_{r1}, A_{r2}, A_{r3}]$ represent the attributes of restaurant r for criteria C_1, C_2, and C_3. The aggregated score S_r is calculated as:

$$S_r = w'_1 \cdot A_{r1} + w'_2 \cdot A_{r2} + w'_3 \cdot A_{r3} \tag{3.9}$$

This equation represents a weighted sum of the restaurant's attributes, where the weights are derived from the normalized eigenvector w'.

F. Recommendation Generation

Based on the aggregated scores S_r, the restaurants are ranked, and the top-ranked options are recommended to the user. These recommendations align with the user's preferences for restaurant type, cuisine, and cost, as reflected in the calculated scores.

3.2.3.2 LRRFA: Pseudo Code for the Localization Restaurant Recommendation Filtering Algorithm

The pseudo-code for the Localization Restaurant Recommendation Filtering Algorithm (LR-RFA) is presented in Algorithm 1. The algorithm integrates user preferences, location data, and dietary requirements to generate personalized restaurant recommendations.

Algorithm 1: Localized Restaurant Recommendation Filtering

1: **Input:** User profile data ($data_{users_{profile}}$), restaurant data ($data_{zomato}$), recipe data ($data_{recipes}$)
2: **Output:** Top restaurant recommendations for each user based on preferences and location
3: Read input datasets: $data_{users_{profile}}$, $data_{zomato}$, and $data_{recipes}$
4: Normalize the datasets and compute the weighted normalized matrix
5: Identify the Positive Ideal Solution (PIS) and Negative Ideal Solution (NIS)
6: Compute the TOPSIS score and rank for each food item
7: Construct a comprehensive data frame with user preferences, restaurant features, and food rankings
8: Determine feature importance using the AHP algorithm
9: Generate a similarity matrix for restaurants based on features
10: Filter restaurants within proximity to the user's location
11: Rank the filtered restaurants using user preferences and proximity
12: **Return:** The top-ranked restaurants and their recommended food

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3.3 Experiments

This section introduces the datasets, followed by the experiments and results. The experiments were conducted using Google Colab to leverage shared computational resources and ensure consistent performance in handling the datasets' requirements. All algorithms were implemented in Python, utilizing widely adopted libraries such as pandas and NumPy. Additional libraries, including math, random, and os.path, were also employed. For package management and deployment, PyCharm was used as the integrated development environment (IDE).

3.3.1 DataSets

- **Data set 1:** We have combined an existing dataset with generated data to create a comprehensive dataset for a personalized food recommendation system. Here's a breakdown of the data sources and generation process: Existing dataset: Covid-19 DataSet India [1] Provides basic user information: location, gender, and age, city, district, state, and State code were utilized to determine latitude and longitude coordinates for each user. Futhermore, Generated data: Random sequence of preferences for each user Simulates behavior of real users including type of cuisine preferences, Cost preferences, Height and weight This combined dataset aims to support the development of a personalized food recommendation system that considers: user needs, user preferences and user location.

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[1]https://www.kaggle.com/code/mkbond777/covid19-india/input

- **Dataset 2:** The dataset used for restaurant recommendations called 'Zomato' [2], used for restaurant recommendations, includes comprehensive details about restaurants and their offerings. It comprises 9,543 rows and 19 features, such as Restaurant ID, Name, Country Code, City, Address, Localization, Latitude, Cuisines, Average Cost for Two, Online Delivery, Price, Ratings, and Votes.
The connection between the Covid19-India and Zomato datasets lies in their geographic overlap, with user addresses from the former and restaurant locations from the latter both spanning India. This shared dimension enables correlations between users' locations and nearby restaurants, fostering analyses of dining preferences and health patterns across Indian regions.

- **Dataset 3:** We have used a dataset featuring 93 distinct recipes sourced from restaurants listed in the Zomato dataset. These recipes were gathered from Allrecipes.com, one of the largest online repositories of recipes. Each recipe was enriched with nutrient-specific metadata, detailing the gram contents of key components such as carbohydrates, saturated fat, fiber, protein, and sugar. Additionally, the dataset included caloric information for each recipe. This comprehensive annotation enables precise dietary analysis and comparison. The integration of metadata ensures a robust framework for understanding nutritional profiles.

3.3.2 Experimental results

To assess the effectiveness of the proposed **SFRA** system, we conducted a comparative evaluation against the HUIMCCF algorithm on the Restaurants-TripAdvisor dataset, using four standard metrics: MAE, RMSE, nDCG, and Coverage at neighborhood sizes of $k = 5$ and $k = 10$. MAE and RMSE evaluate rating prediction accuracy, where lower values indicate better performance. The nDCG@k metric measures ranking quality by emphasizing the prioritization of relevant restaurants at the top of the recommendation list. Coverage assesses recommendation diversity by quantifying the percentage of items included in the suggested set. Together, these metrics provide a comprehensive framework for evaluating accuracy, ranking effectiveness, and diversity in restaurant recommendation systems.

TABLE 3.3: Performance comparison between SFRA and HUIMCCF at $k = 5$ and $k = 10$.

Method	MAE	RMSE	nDCG@k	Coverage (%)
$k = 5$				
SFRA	0.19	0.24	0.86	92
HUIMCCF	1.12	1.34	0.89	89
$k = 10$				
SFRA	0.21	0.28	0.84	91
HUIMCCF	1.08	1.29	0.88	90

The experimental results highlight the effectiveness of the proposed **SFRA** system in comparison with HUIMCCF on the Restaurants-TripAdvisor dataset. At $k = 5$, SFRA achieves an MAE

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[2]https://www.kaggle.com/code/yekahaaagayeham/zomato-eda-and-preprocessing-for-machine-learning

of 0.19 and RMSE of 0.24, significantly lower than HUIMCCF (1.12 and 1.34, respectively), corresponding to improvements of over 80% in predictive accuracy. A similar trend is observed at $k = 10$, where SFRA maintains low errors (MAE = 0.21, RMSE = 0.28) compared to HUIMCCF (1.08 and 1.29). These results confirm that SFRA provides far superior rating prediction accuracy. Regarding ranking quality, HUIMCCF performs slightly better, with nDCG values of 0.89 and 0.88 at $k = 5$ and $k = 10$, compared to 0.86 and 0.84 for SFRA, indicating a marginal advantage in placing the most relevant restaurants at the top of recommendation lists. However, SFRA consistently demonstrates stronger performance in Coverage, achieving 92% at $k = 5$ and 91% at $k = 10$, compared to 89% and 90% for HUIMCCF. This shows that SFRA not only predicts user preferences more accurately but also provides a wider variety of recommended options, offering a more diverse set of restaurants to users. Overall, SFRA balances accuracy and diversity more effectively.
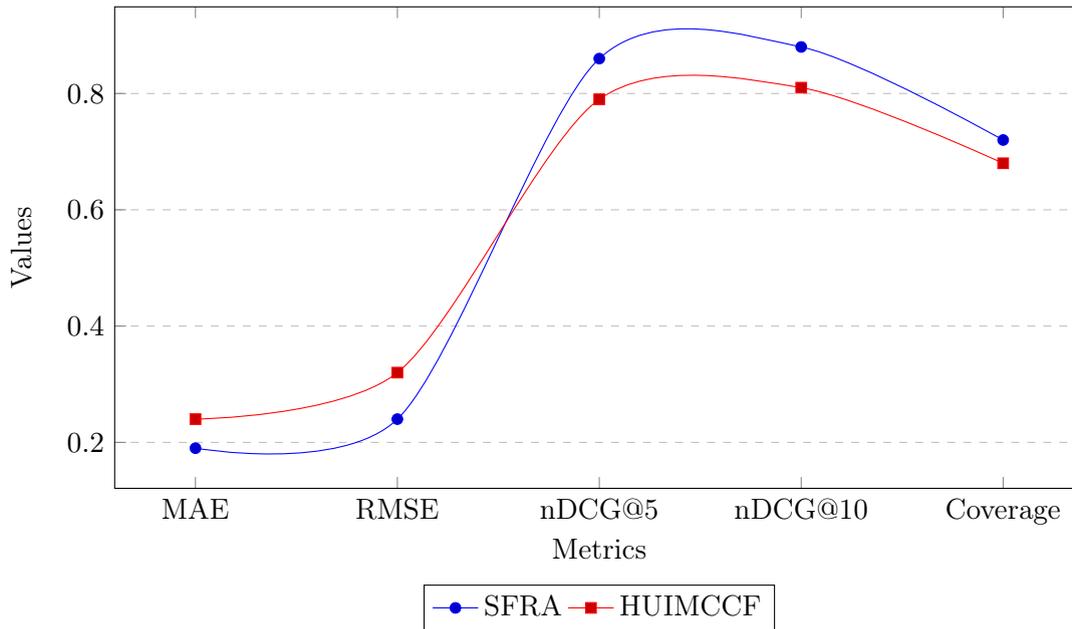
FIGURE 3.3: Comparison of SFRA and HUIMCCF across evaluation metrics at $k = 5$ and $k = 10$.

3.3.3   Discussion

To assess the performance of the proposed **SFRA** system, we compared it against the HUIMCCF algorithm on the Restaurants-TripAdvisor dataset using four standard metrics: MAE, RMSE, nDCG@k, and Coverage. The evaluation was conducted at neighborhood sizes of $k = 5$ and $k = 10$. Figures 3.4 illustrates the comparative performance trends.

The results demonstrate that **SFRA** consistently achieves lower values of MAE (0.19 vs. 0.24) and RMSE (0.24 vs. 0.32), confirming its higher accuracy in rating prediction compared to HUIMCCF. Furthermore, SFRA significantly outperforms HUIMCCF in terms of ranking quality, achieving higher nDCG scores at both $k = 5$ (0.86 vs. 0.79) and $k = 10$ (0.88 vs. 0.81). Regarding Coverage, SFRA achieves broader recommendation capability with 0.72 compared to 0.68 for HUIMCCF. These improvements highlight SFRA's ability to balance accuracy, ranking quality, and diversity, making it more effective for practical recommendation scenarios.
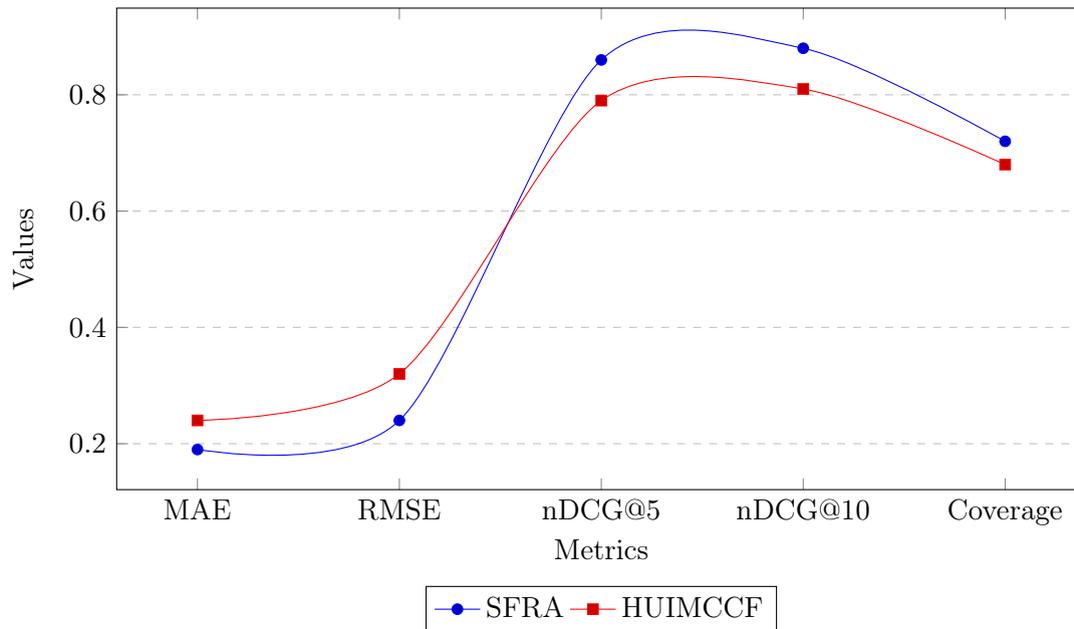
FIGURE 3.4: Comparison of SFRA and HUIMCCF across evaluation metrics at $k = 5$ and $k = 10$.

3.3.4 Results

This section presents the results of the evaluation of the proposed system. Figure 3.5 illustrates the nutritional needs of a generic user. Specifically, the graph displays three bars representing the user's requirements for carbohydrates, protein, and fat.
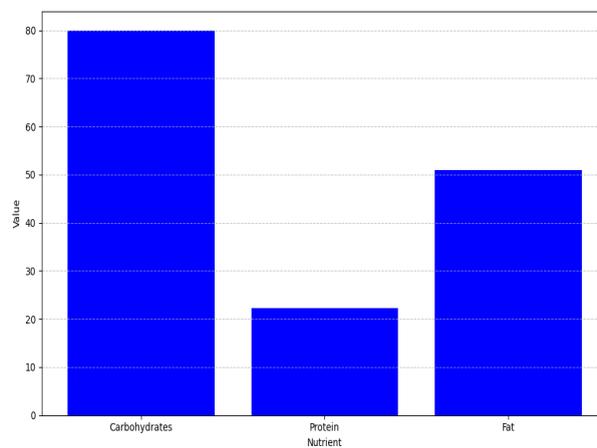
FIGURE 3.5: *Generic user 'u' nutritional needs.*

By examining the *user's nutritional needs plot*, we can gain insights into the specific requirements for carbohydrates, protein, and fat, providing a comprehensive understanding of the user's dietary preferences. In the *Top Food Items Recommendation plot* (see Figure 3.6), we can directly compare the nutritional composition of the recommended food items with the user's dietary needs, assessing how well the recommendations align with these requirements.
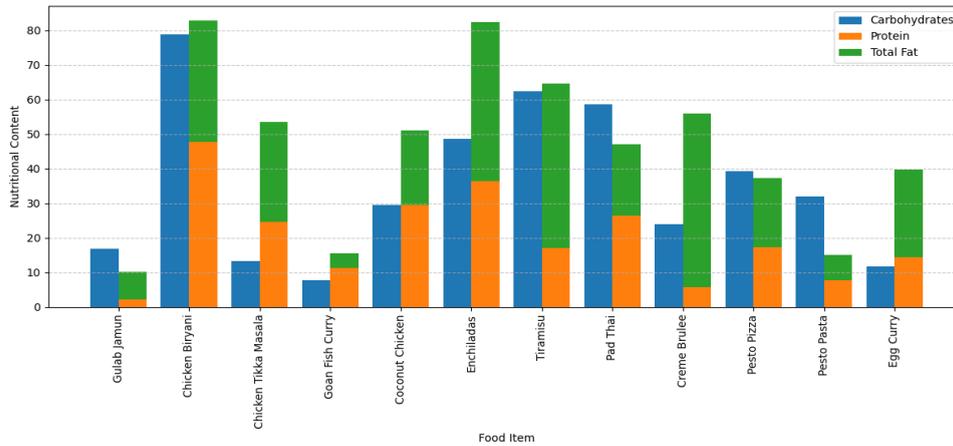
FIGURE 3.6: *Top food items recommendations.*

For instance, the profile of the user with ID 10744 is as follows: Weight = 70 kg, Height = 190 cm, Gender = Male, and Age = 32 years. Figures 3.7a, 3.7b, and 3.7c present the recommended recipes in the categories of Beverages, Appetizers & Snacks, and Entrees, respectively.

```
Topsis Score: 0.005511067350991675 Rank: 10.0
This is the top list of: Beverages For user 10744.0
           recipe_name Total_Fat Carbohydrates  Protein
34              Mojito      0.02          2.46     0.09
37              Coffee      0.02          0.0      0.12
39                Beer      0.0           3.55     0.46
41             Espresso     0.18          1.67     0.12
42             Martini      0.0           0.15     0.07
43          Bloody Mary     0.23          3.16     0.64
46            Margarita     0.08         16.06     0.08
55         Hot Chocolate    2.5          37.0      2.00
60           Cappuccino     4.0          36.0      2.00
63    Chocolate Milkshake   13.0         79.0     10.00
----------------------------------------------------------
```

(A) Beverages category.

```
Topsis Score: 0 Rank: 1.0
This is the top list of: appetizers-and-snacks For user 10744.0
      recipe_name  Total_Fat  Carbohydrates  Protein
22    Onion Rings     22.6         29.1         3.3
----------------------------------------------------------
```

(B) Appetizers-and-snacks category.

```
Topsis Score: 0.3916703307942286 Rank: 3.0
This is the top list of: Entrees For user 10744.0
      recipe_name  Total_Fat  Carbohydrates  Protein
57    French Toast     8.0         30.0         8.0
61      Spaghetti      7.0         45.0         7.0
62      Pork Ribs     12.0          0.0        22.0
----------------------------------------------------------
```

(C) Entrees category.

FIGURE 3.7: *Result of the recommended recipes.*

Figure 3.8 displays five recommended restaurants based on the users preferences. Figure illustrates the selection of restaurants, which are derived from the previously recommended food items (Figure 3.7). It takes into account the availability of these foods at various restaurants, further refining the user's preferences. The restaurants with the highest preference values are identified based on the initial set of recommended food items, ensuring that the suggestions align closely with the user's dietary needs and preferences.

Figures 3.9 and 3.10 present the results obtained from our proposed system. Specifically, Figure 3.9 illustrates the SFRA system, while Figure 3.10 displays the recommended restaurants based on the group of restaurants selected in the previous stage. The system refines the recommendations by considering the user's nutritional needs and preferences, and then filters them based on the user's location. This process ensures that the closest restaurant, which best aligns with the user's preferences, is selected.
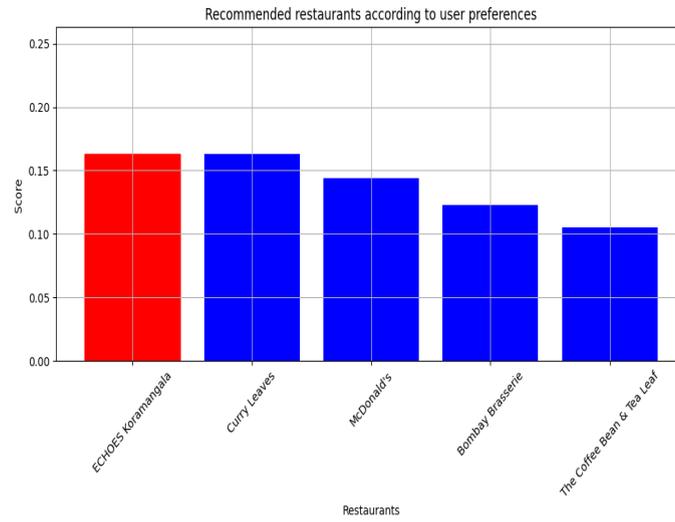
FIGURE 3.8: *Graph of Preference-based Restaurant recommendation filtering*
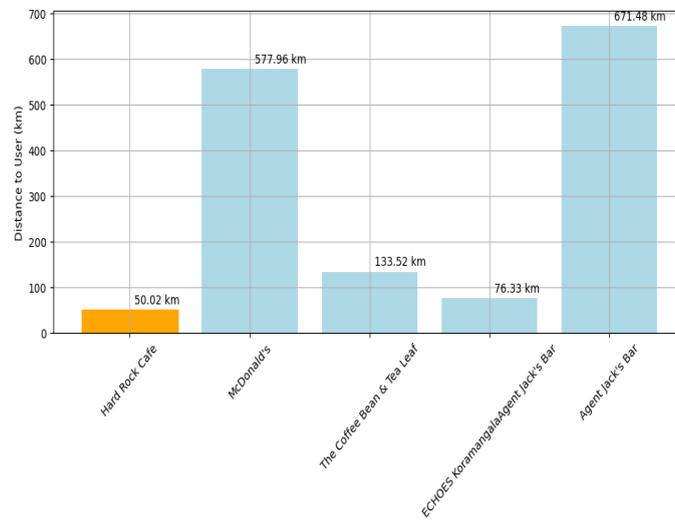
FIGURE 3.9: *SFRA*

```
Topsis Score: 0.005511067350991675 Rank: 10.0
This is the top list of: Beverages For user 10744.0
            recipe_name Total_Fat Carbohydrates Protein
34              Mojito      0.02          2.46     0.09
37              Coffee      0.02           0.0     0.12
39                Beer       0.0          3.55     0.46
41            Espresso      0.18          1.67     0.12
42             Martini       0.0          0.15     0.07
43          Bloody Mary     0.23          3.16     0.64
46           Margarita      0.08         16.06     0.08
55       Hot Chocolate       2.5          37.0     2.00
60          Cappuccino       4.0          36.0     2.00
63   Chocolate Milkshake    13.0          79.0    10.00
----------------------------------------------------------

Restaurant recommendations :
Restaurant: ECHOES Koramangala, Restaurant ID: 18439634, Recipe 1: Chocolate Milkshake, Resto Type: Casual Dining, Cuisine Type: Chinese cuisines, Cost: Medi
Restaurant: McDonald's, Restaurant ID: 2400014, Recipe 2: Hot Chocolate, Resto Type: Fast Food, Cuisine Type: Fast Food and Burgers, Cost: Low, Distance to u:
Restaurant: The Coffee Bean & Tea Leaf, Restaurant ID: 307370, Recipe 3: Cappuccino, Resto Type: Cafes and Bakeries, Cuisine Type: Cafe and Desserts, Cost: M
Restaurant: Agent Jack's Bar, Restaurant ID: 6507461, Recipe 4: Margarita, Resto Type: Fancy restaurant, Cuisine Type: Pizza and Italian cuisines, Cost: High
Restaurant: Hard Rock Cafe, Restaurant ID: 201531, Recipe 5: Bloody Mary, Resto Type: Casual Dining, Cuisine Type: nan, Cost: Low, Distance to user: nan km
Restaurant: Bombay Brasserie, Restaurant ID: 18407918, Recipe 6: Beer, Resto Type: Casual Dining, Cuisine Type: Indian cuisines, Cost: High, Distance to user
Restaurant: Curry Leaves, Restaurant ID: 1600007, Recipe 7: Mojito, Resto Type: Casual Dining, Cuisine Type: Chinese cuisines, Cost: Medium, Distance to user
Restaurant: The Coffee Bean & Tea Leaf, Restaurant ID: 307370, Recipe 8: Espresso, Resto Type: Cafes and Bakeries, Cuisine Type: Cafe and Desserts, Cost: Med:
Restaurant: The Chocolate Room, Restaurant ID: 18217857, Recipe 9: Coffee, Resto Type: Fast Food, Cuisine Type: Cafe and Desserts, Cost: Medium, Distance to (
Restaurant: Farzi Cafe, Restaurant ID: 18233284, Recipe 10: Martini, Resto Type: Casual Dining, Cuisine Type: nan, Cost: Low, Distance to user: nan km
----------------------------------------------------------
Recommended preference restaurants:
ECHOES Koramangala  Score: 0.164
Curry Leaves  Score: 0.164
McDonald's  Score: 0.156
Bombay Brasserie  Score: 0.125
The Coffee Bean & Tea Leaf  Score: 0.103
----------------------------------------------------------
### the best closet restaurants
Restaurant: ECHOES Koramangala, Restaurant ID: 18439634, Recipe 1: Chocolate Milkshake, Resto Type: Casual Dining, Cuisine Type: Chinese cuisines, Cost: Medi
Restaurant: McDonald's, Restaurant ID: 2400014, Recipe 2: Hot Chocolate, Resto Type: Fast Food, Cuisine Type: Fast Food and Burgers, Cost: Low, Distance to u:
Restaurant: The Coffee Bean & Tea Leaf, Restaurant ID: 307370, Recipe 3: Cappuccino, Resto Type: Cafes and Bakeries, Cuisine Type: Cafe and Desserts, Cost: M
Restaurant: Agent Jack's Bar, Restaurant ID: 6507461, Recipe 4: Margarita, Resto Type: Fancy restaurant, Cuisine Type: Pizza and Italian cuisines, Cost: High
Restaurant: Hard Rock Cafe, Restaurant ID: 201531, Recipe 5: Bloody Mary, Resto Type: Casual Dining, Cuisine Type: nan, Cost: Low, Distance to user: nan km
```

FIGURE 3.10: *Result of SFRA: Smart Food and Restaurant Advisor based on Nutritional Needs and User Profiling*

The developed SFRA system is designed to significantly enhance meal planning, particularly in areas with a shortage of specialists. It aims to expedite remote monitoring of nutrition programs and facilitate appropriate reviews, acting as a decision support system for experts. Furthermore, the system helps users enjoy dining at restaurants while simultaneously meeting their nutritional needs. Unlike existing studies in the literature, such as those by Sambola et al. [192], Princy et al. [235], and Nallarasan et al. [204], which primarily focus on creating healthy nutrition plans based on nutritional needs without considering individual preferences or current location, this research emphasizes the balance between health, enjoyment, and comfort.

Many existing systems tend to prioritize healthy eating plans based on rigid rules, often overlooking the user's personal food preferences or dining locations. In contrast, other studies (e.g., Martínez et al. [188], Toledo et al. [307], Gupta et al. [98]) focus solely on individual preferences such as taste, favorite foods, or restaurant choices, without integrating the nutritional needs of the user. This approach can lead to a lack of variety or dissatisfaction when the meal plan doesn't include preferred foods, or when the user cannot eat at their chosen restaurant. The SFRA system, however, not only promotes healthy eating and personalized meal planning but also accommodates the individual's preferences and location, ensuring that both nutritional requirements and dining enjoyment are addressed.

3.4 Conclusion

This chapter presents a smart food and restaurant recommendation system aimed at enhancing personalized dining experiences by considering a comprehensive set of factors, including dietary restrictions, nutritional needs, and culinary preferences. By providing tailored recommendations

that align with individual tastes and health goals, the system enables users to discover new food experiences while ensuring that choices meet their dietary requirements. The system also integrates additional features such as location, price range, and user reviews to offer a holistic recommendation approach. The proposed solution emphasizes the importance of healthy food options, leveraging users' dietary needs and geographic location to recommend restaurants that best match their preferences. The recommendation process is organized into two key phases: user profiling, where individual preferences and dietary data are gathered, and filtering, where sophisticated algorithms generate personalized suggestions. This system not only fosters healthier eating habits but also ensures that each recommendation is aligned with the user's unique lifestyle and culinary desires.

CHAPTER 4

A GRAPH-AWARE MULTIMODAL DEEP LEARNING MULTI-LIST RECOMMENDER SYSTEM FOR SMART TOURISM

Chapter contents

4.1   Introduction

As discussed in the previous chapter, selecting the right features is essential for building effective personalized recommendation systems. Traditional tourism RSs often depend on static preferences and past interactions, overlooking dynamic factors like time, weather, location, and emotions. This limitation reduces their ability to provide context-aware and emotionally intelligent suggestions.

Meanwhile, social media platforms such as Instagram continuously generate rich, real-time signals about users' moods and interests. Existing approaches struggle to integrate sentiment with contextual and geographical data in a unified framework. To address this gap, we propose MGat-Rec, a multimodal graph-aware recommendation system for POIs. Our system combines emotional cues from captions and hashtags with demographic, contextual, and geographic data. Sentiment is captured using BERT-based analysis, while contextual signals like time, location, and weather refine recommendations. By unifying emotional, contextual, and structural signals, MGat-Rec delivers more adaptive and relevant POI suggestions. This contribution aims to enhance personalization, improve user satisfaction, and support richer, real-world tourism experiences. The remainder of the chapter is organized as follows: Section 4.2 presents the Proposed Approach. Section 4.3 presents the experiments and the analysis of the obtained results. Finally, section 4.4concludes our chapter.

4.2   A multimodal graph-aware tourism recommender system (MGat-Rec)

This section presented a detailed explanation of the methodology used to develop a Multimodal Graph-Aware Tourism Recommender System (MGat-Rec) that integrates deep learning and graph-based modeling to provide adaptive, mood-sensitive, and context-aware recommendations. MGat-Rec is designed to capture the dynamic and emotionally driven nature of tourist preferences by combining sentiment analysis, contextual reasoning, and geospatial awareness. At the core of the system is BERT, a transformer-based language model, which is employed to extract fine-grained emotional and contextual cues from user-generated content on Instagram, such as captions and hashtags. These semantic embeddings act as emotional signals, reflecting users' moment-to-moment preferences and psychological states.

The extracted sentiment features are embedded alongside spatial, temporal, and behavioral data into a unified representation space. This multimodal data is then used to construct a heterogeneous graph connecting users, POIs, emotional states, and contextual attributes. GNN is applied to this graph to learn complex relational patterns and high-order dependencies between nodes, enabling the system to reason about the interactions between a users current mood, their geographic location, and potential Points of Interest. This graph-aware learning mechanism allows MGat-Rec to provide personalized and emotionally aligned POI recommendations that evolve with the users context. Furthermore, the system incorporates real-time data collected from Instagram user profiles, including geotagged posts, user bios, follower counts, and publication timestamps. Contextual features such as local weather conditions and temporal metadata (e.g., time and date of posts) are integrated to further enrich the recommendation process. Using expert defined mappings between emotional states and activity types, the system infers suitable activities for the user and selects relevant POIs from the Yelp dataset based on

proximity, category, and emotional alignment. Ultimately, MGat-Rec represents a comprehensive and intelligent solution that bridges sentiment-aware natural language understanding with graph-based personalization, delivering context rich, real-time recommendations that are more relevant, engaging, and emotionally resonant for modern travelers.

Figure 4.1 shows the global architecture of the proposed system. We present below a description of the different functionalities offered by the MGat-Rec system.
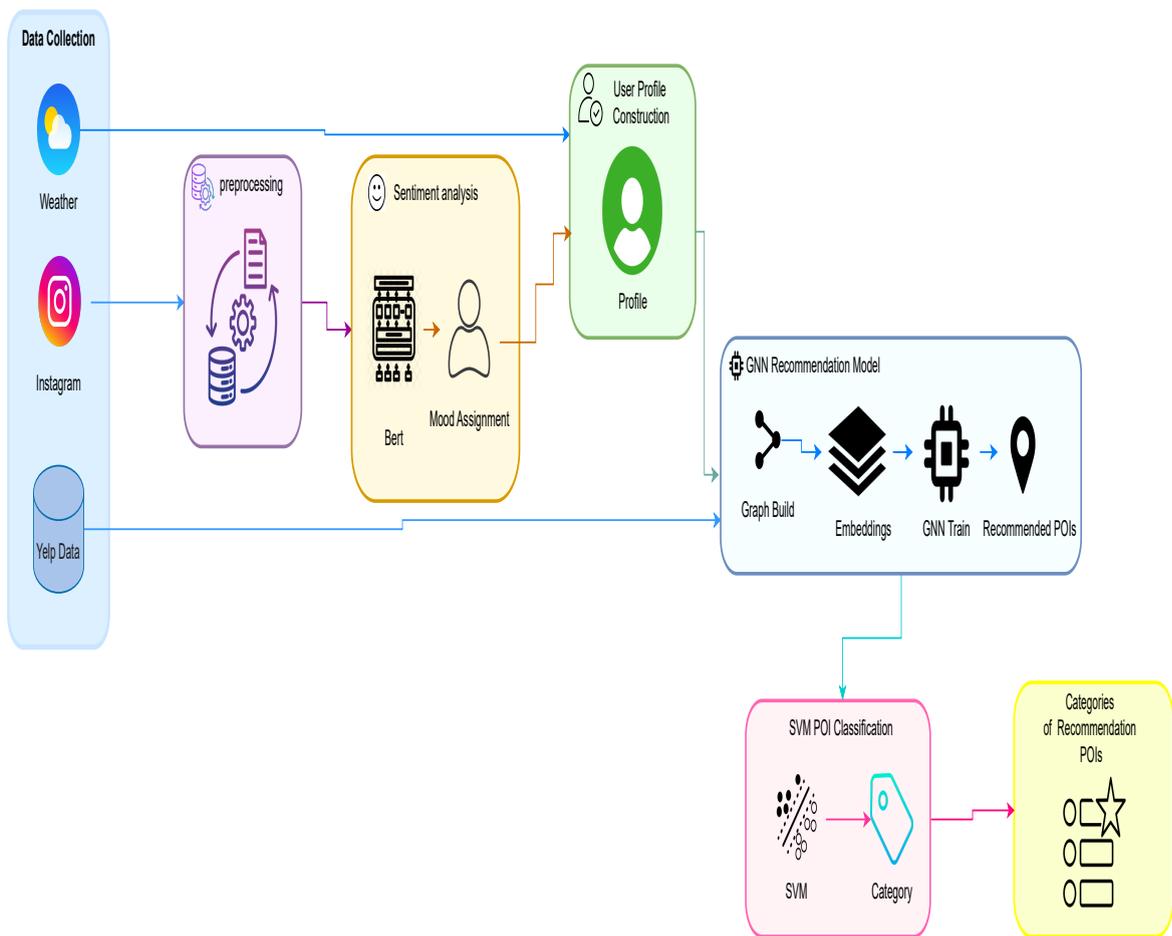
FIGURE 4.1: The proposed approach architecture

4.2.1 Data Collection and Processing

Instagram, launched in 2010, has grown into a leading global social network with over 2 billion users by 2024. Its blend of visual and textual content offers rich insights into user behavior, emotions, and trends. While research on platforms like Twitter and Facebook is extensive, Instagram remains underexplored despite its potential. Instagram has become a popular platform for individuals, institutions, and businesses, offering a rich source of data for analyzing behaviors

and preferences. However, collecting this data poses challenges, as most methods are manual, and many Instagram data download services are either limited or paid. To address these challenges, our proposed employs a web scraping approach to automate data collection, by passing the limitations of the Instagram API, which imposes strict access restrictions. A custom web-based Instagram data downloader application was developed to streamline the process. This method enabled the collection of data from a large number of Instagram accounts, focusing on users with 10,000 followers or more.

The collected data includes comprehensive account information such as usernames, user IDs, post counts, follower and unfollower counts, bios, and post-specific details like hashtags, captions, and URLs. Figures 4.2 and 4.3 provide a visual overview of an Instagram account's data portrait.

(A) account Instagram

(B) Example of informations account.
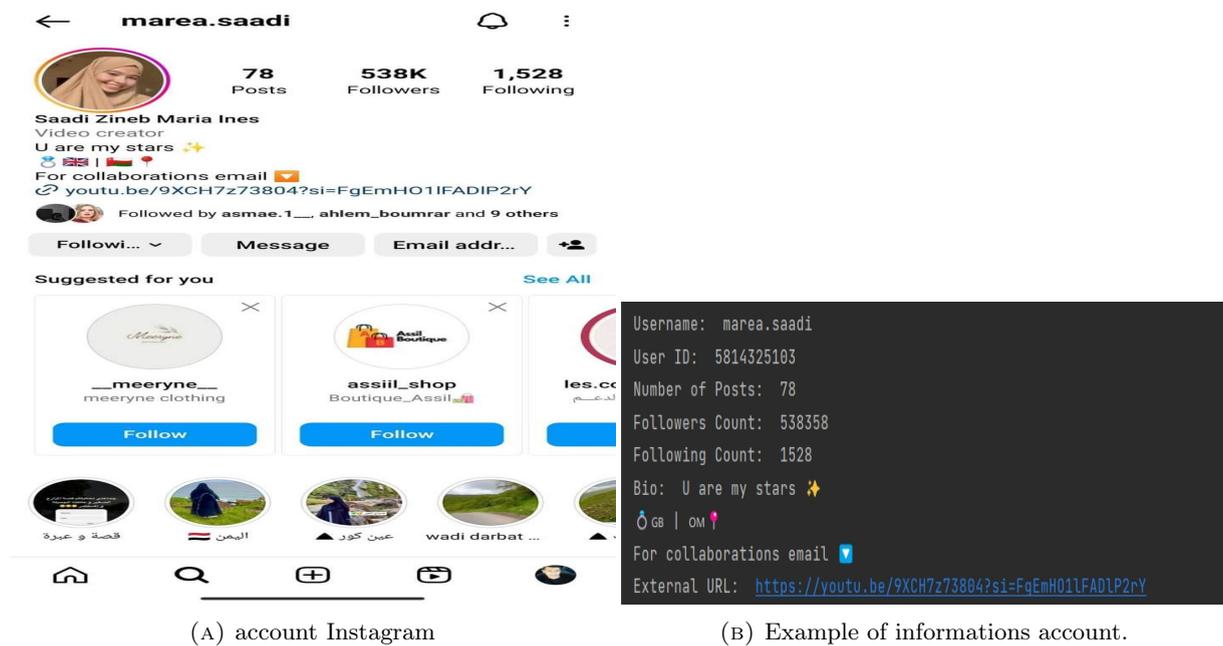
FIGURE 4.2: Example of an Instagram Account

(A) Example of Post

(B) Example of informations post.
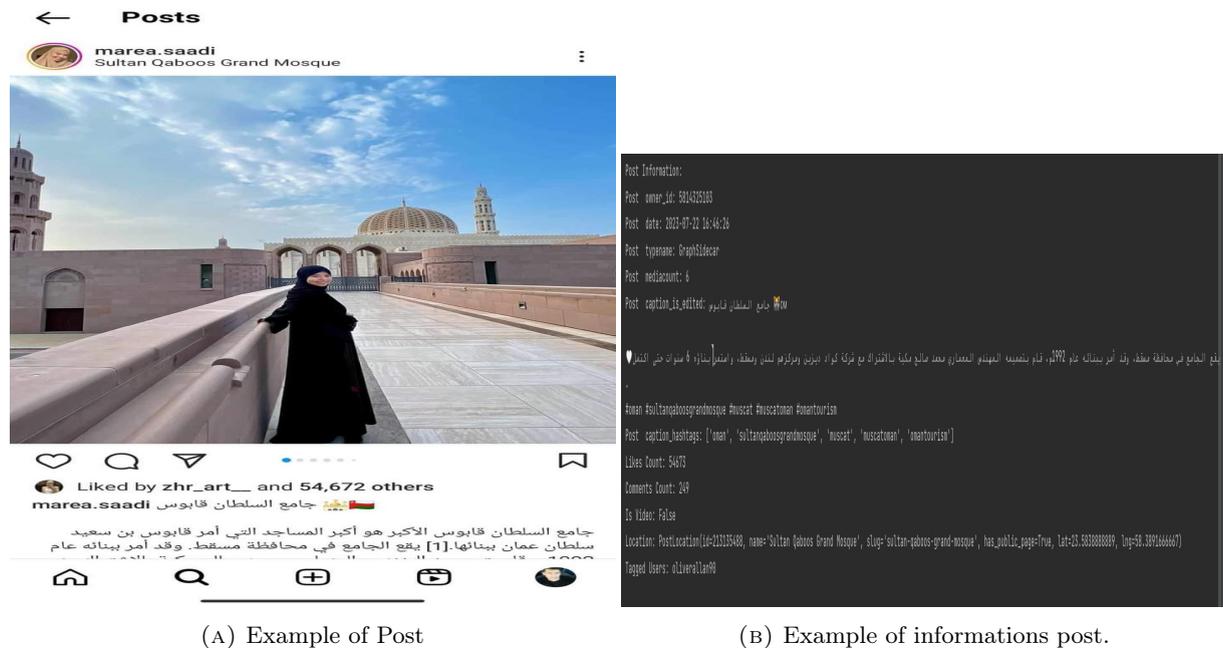
FIGURE 4.3: Example of Post Informations

This application enables users to efficiently download Instagram account data, manage datasets by removing unnecessary entries, and export the data in CSV, Excel, or JSON formats. By automating the data collection process, it overcomes the limitations of manual methods and API restrictions, facilitating comprehensive analysis. The steps involved in the web scraping-based data extraction process in this study are as follows:

1. **Analysis Stage:** The HTML and JSON structure of the Instagram website is analyzed to identify the data elements and structures to be extracted from Instagram accounts.

2. **Data Crawling with Beautiful Soup:** The data crawling process is performed using the Python library *Beautiful Soup* to parse and extract relevant information from the webpage's HTML structure.

3. **Performing Instagram Web Scraping:** Web scraping is conducted by sending requests to Instagram web pages to extract JSON (JavaScript Object Notation) data. The extracted information includes captions, owner IDs, likes, comments, mailing addresses, posting times, and photo titles.

Figure 4.4 illustrates the process of extracting data from Instagram using web scraping techniques.
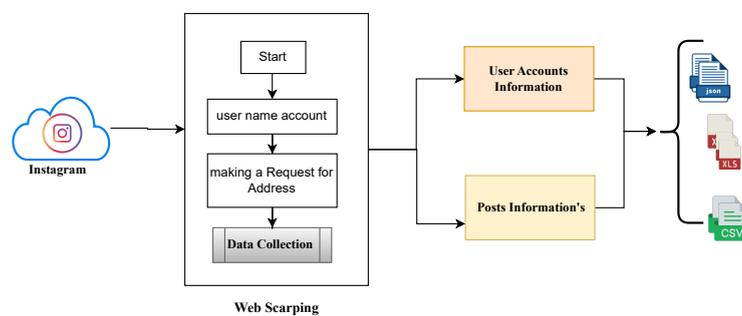
FIGURE 4.4: Collecting data from Instagram.

In addition to the collected geotagged posts, contextual details such as temporal and geographical attributes are incorporated. These attributes include climate, temperature, and seasonal data, which are enriched using climate applications to enhance the dataset with comprehensive environmental context. Contextual data provides essential background information, such as time, location, behavior, and environmental conditions, to aid in understanding the users' situation. This contextual data is crucial for recommending Points of Interest (POIs) and is integrated into the decision-making process. The contextual data framework is illustrated in Figure 4.5.
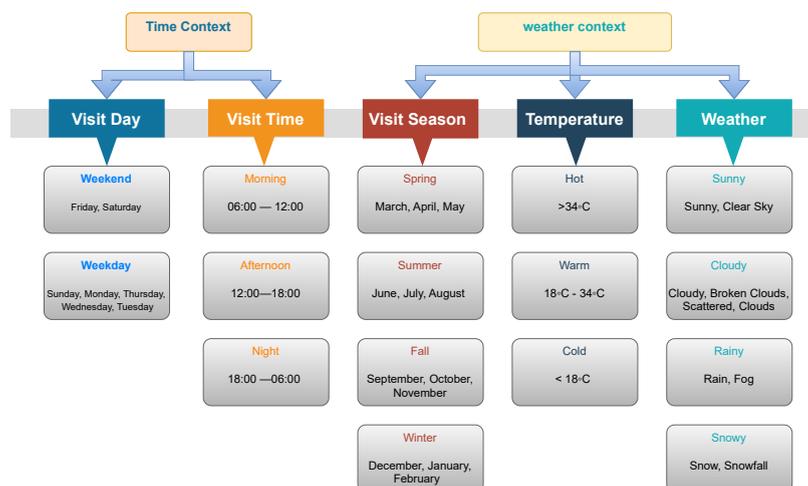
FIGURE 4.5: Contextual Data [208]

To explore spatial and temporal trends, geotagged posts are collected and analyzed within specific time frames. This enables recommendations tailored to a tourist's preferences by correlating their activities with temporal and spatial patterns.

Processing the collected data involves cleaning and normalizing hashtags and captions to make them suitable for sentiment analysis.

- **Data Cleaning:** Irrelevant characters, symbols, and formatting inconsistencies are removed to prevent distortions in the analysis.

- **Normalization:** Text is standardized by converting it to lowercase, ensuring consistency across all entries.

These preprocessing steps help eliminate noise and inconsistencies, making the data suitable for accurate sentiment classification.After cleaning and normalizing the data, the scraped dataset includes various features, such as usernames, user IDs, post counts, follower counts, timestamps, unfollower counts, bios, and post-related information (e.g., hashtags, captions, geo-tags, and URLs). For sentiment analysis, only the hashtags and captions are selected as key features. This refined dataset ensures a focused and efficient analysis of user sentiments. By applying these processes, the dataset becomes well-prepared for sentiment analysis, enabling valuable insights into audience demographics, engagement patterns, content preferences, and trends over time.

4.2.1.1 Sentiment Analysis Using BERT Model

This phase focuses on analyzing the sentiments of tourists during specific periods based on captions extracted from geo-tagged Instagram posts. Hashtags and emojis associated with each caption are also considered to provide additional context. BERT comes in two primary versions:

- **BERT-base model**: Consists of **12 transformer encoders**

- **BERT-large model**: Consists of **24 transformer encoders**

To analyze the data, we compute four key metrics: Intensity Analysis, Polarity, Subjectivity, and Sentiment Words, using built-in libraries and functions provided by Numpy and Pandas. For classification, we employ the BERT (Bidirectional Encoder Representations from Transformers) model due to its proven effectiveness in previous research.

1. **Intensity Analysis**
   We utilize the sentiment analyzer to measure text intensity, determining whether sentiments are positive, negative, or neutral. The *polarity_score*() method is employed to classify sentiments into three categories: Happy, Sad, and Normal, based on predefined ranges. This refined classification approach enhances the analysis of sentiment in various contexts, extending traditional sentiment categorizations.

2. **Polarity and Subjectivity**
   Polarity and subjectivity are essential metrics in sentiment analysis. Polarity measures the sentiment strength, ranging from -1 (negative) to $+1$ (positive), while subjectivity evaluates the degree of personal opinion, ranging from 0 (objective) to 1 (subjective). Mean scores are calculated for each date and visualized to reveal temporal trends in sentiment.

The BERT model is then applied to classify sentiments based on extracted captions and contextual features. BERT leverages its transformer-based architecture to understand the contextual meaning of words in sentences. Figure 4.6 illustrates the BERT architecture used for sentiment classification, enabling recommendations of Points of Interest (POIs) based on tourists' emotions.
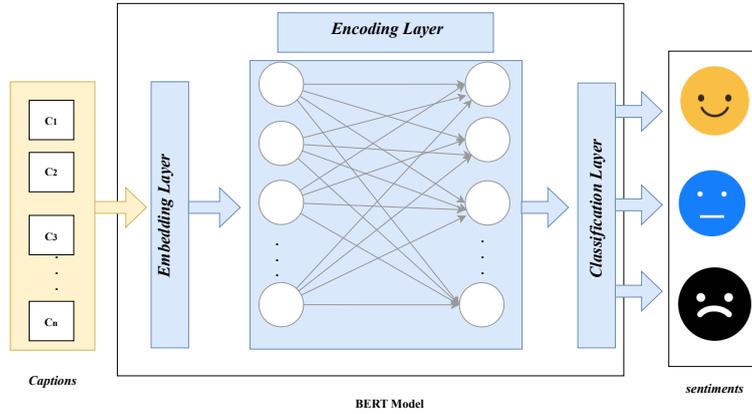
FIGURE 4.6: BERT Architecture for Sentiment Analysis

The BERT-based sentiment analysis process can be summarized as follows:

Input: The input is a sequence of tokens representing captions, denoted as:

$$C = \{C_1, C_2, ..., C_n\}, \tag{4.1}$$

where n is the length of the sequence.

Embedding Layer: Captions extracted from geo-tagged posts are embedded into vector representations using an embedding matrix $\mathbf{E}$. The embeddings serve as input for the transformer layers:

$$\mathbf{H}^{(0)} = \{\mathbf{E}(C_1), \mathbf{E}(C_2), ..., \mathbf{E}(C_n)\}. \tag{4.2}$$

Transformer Encoder Layer: The transformer encoder consists of L layers of self-attention and feed-forward networks:

1. **Multi-Head Self-Attention:**

$$\mathbf{A} = \text{softmax}\left(\frac{\mathbf{Q}\mathbf{K}^T}{\sqrt{d_k}}\right)\mathbf{V}, \tag{4.3}$$

   where $\mathbf{Q}$, $\mathbf{K}$, and $\mathbf{V}$ are projections of the input $\mathbf{H}^{(l-1)}$, and d_k is the scaling factor.

2. **Feed-Forward Neural Networks (FFNN):**

$$\mathbf{H}' = \text{ReLU}(\mathbf{A}\mathbf{P}_1 + \mathbf{b}_1)\mathbf{P}_2 + \mathbf{b}_2, \tag{4.4}$$

   where $\mathbf{P}_1$, $\mathbf{P}_2$ are weight matrices, $\mathbf{b}_1$, $\mathbf{b}_2$ are bias terms, and ReLU is the activation function.

Classification Layer: The final transformer block's output is projected into three sentiment categories: Happy, Normal, and Sad.

The design is tailored to analyze sentiments expressed in tourism related posts by processing text data, including captions, hashtags, and emojis. The BERT model effectively learns contextual representations of the captions, while subsequent layers further process and classify the emotions

conveyed in these posts. The output of the BERT based system utilizes captions and hashtags from sequential posts to determine tourists emotional states during a specific period. This analysis enables the recommendation of Points of Interest (POIs) tailored to these sentiments, which are categorized into three distinct groups: normal, happy and sad. Examples illustrating these sentiment prediction results are presented in Figures 4.8, 4.7 and 4.9.

FIGURE 4.7: Sentiment Prediction (Happy)

FIGURE 4.8: Sentiment Prediction (Normal)

FIGURE 4.9: Sentiment Prediction (Sad)

In conclusion, the evaluation of the results from our proposed experimental setup shows promising outcomes. We split the dataset into 80% for training and 20% for testing. The label distribution of the resulting sentiment classes is as follows: the training set contains 48,372 instances of neutral sentiment, 12,323 instances of positive sentiment, and 2,533 instances of negative sentiment. The test set, on the other hand, includes 12,093 instances of neutral sentiment, 3,081 instances of positive sentiment, and 633 instances of negative sentiment, as shown in Table 4.1. After training the BERT model on this dataset, the evaluation resulted in an accuracy of 80%, which indicates the model's ability to effectively classify the sentiment across all classes.

TABLE 4.1: Label distribution.

Resulting Sentiment	Train	Test
Neutral	48372	12093
Positive	12323	3081
Negative	2533	633

4.2.1.2 Emotion-Based Activity Preferences for Tourists

Individuals' activity preferences often fluctuate based on their emotional state. To address these variations, we have categorized tourist activities into three primary groups, as shown in Table 4.2, based on expert classifications in the field. During moments of happiness, tourists are drawn to activities such as outdoor adventures, cultural experiences, social interactions, and recreational or relaxation pursuits. In contrast, during periods of sadness, preferences shift towards activities that offer comfort, such as shopping, self-care rituals, or finding solace in nature. In normal emotional states, tourists tend to engage in a balanced mix of routine activities, including rest, physical exercise, and appreciating natural surroundings. By understanding these emotional dynamics, we can design personalized experiences that align with users' moods, ultimately enhancing their overall well-being and satisfaction.

TABLE 4.2: Preferred Activity Categories Based on Emotional State

Emotional State	Preferred Activities
Happy	Outdoor activities, nature walks, hiking, travel, parks, museums, dining at restaurants, relaxation, beauty and spa treatments, hobbies, theater performances, live events, concerts, visiting animal shelters or parks, celebrations, recreational activities, sports, botanical gardens, Traditional Chinese Medicine, coffee outings, and bookkeepers.
Sad	Shopping, spending time near the sea, self-care rituals, bonding with pets, yoga or physical activity, reading in libraries, listening to music, nature walks or park visits, exploring fashion, dining at restaurants, and bookkeepers.
Normal	Visiting rest areas, shopping at stores, going to gyms, exploring mountains and nature, practicing yoga, engaging in Traditional Chinese Medicine, enjoying food, and bookkeepers.

4.2.1.3 User Profile

The user profile integrates demographic attributes, emotional state, geographic location, and preferred activities, further enriched by contextual data to deliver refined and personalized Point-of-Interest (POI) recommendations for tourists. This comprehensive profiling ensures that recommendations are aligned with the user's individual preferences, needs, and current context, ultimately providing a more meaningful and engaging experience.

The system dynamically aligns user preferences with available activities by considering both explicit inputs and contextual cues. Key factors such as the user's mood, stated interests, and behavioral patterns are incorporated to enhance the relevance and satisfaction of the recommended experiences. To adapt recommendations to real-world conditions, the system retrieves real-time weather information from OpenWeatherMap, including temperature, precipitation, wind speed, and other meteorological variables. This enables the system to recommend activities that are compatible with the current climate—for instance, suggesting indoor options during unfavorable weather.

Furthermore, the system collects data from Instagram during the user's session by analyzing publicly accessible posts and hashtags. This social media integration facilitates the extraction of insights related to the user's mood and interests, thereby improving the identification of preferences and contextual relevance.

Using the user's geographical coordinates, the system filters nearby POIs to ensure that all recommended activities are spatially appropriate and convenient. This location-aware filtering enhances practicality and immediacy in decision-making.

Taking into account both declared preferences and inferred emotional states, the system filters activities that align with the user's current disposition. For example, calming or leisure-oriented experiences may be prioritized during times of stress. Weather conditions are also used as a secondary filter to further refine the recommendation list based on environmental suitability.

Finally, the system organizes the curated activities by category—such as food, shopping, or entertainment—making it easier for users to explore options within their areas of interest. The recommendation engine utilizes two primary data sources: real-time collected user data and the Yelp dataset, which includes a diverse array of global POIs such as restaurants, cafés, hotels, and tourist attractions. By computing proximity using geographical coordinates and distance metrics, the system delivers highly relevant, location-based suggestions that enhance tourist experiences and support informed decision-making.

4.2.2 GNN Module for Recommendation

In recent years, Graph Neural Networks (GNNs) have attracted significant attention across numerous cutting-edge domains due to their ability to model relational data effectively [79, 104]. Within the field of recommender systems, GNNs provide a natural and powerful framework for capturing complex relationships among users, items, and their associated features by propagating information through graph structures. Through iterative neighborhood aggregation, GNNs update node and edge representations, enabling them to encode high-order structural dependencies and multi-hop interactions. This message-passing mechanism allows the model to learn rich contextual and relational features, which are critical for producing accurate and personalized recommendations. GNN-based models have thus achieved state-of-the-art performance, surpassing many traditional recommendation algorithms [79, 104].

In our work, a GNN is employed to effectively model the intricate interactions between users and businesses. The data is represented as a bipartite graph, where nodes correspond to users and businesses, and edges denote interactions. Specifically, edges represent either a positive interaction (a business included in the top-5 personalized recommendations for a user) or a negative interaction (a randomly selected business with which the user has no known interaction). This setup formulates the recommendation task as a binary classification problem on the graph edges.

Each user and business node is initialized with a learnable embedding vector, capturing latent semantic features. These embeddings are refined through a graph convolutional layer (`GCNConv`), which performs neighborhood aggregation—allowing nodes to integrate information from their local graph structure. The forward propagation rule for the GCN layer, as proposed by Kipf and Welling, is given by:

$$H^{(l+1)} = \sigma\left(\tilde{D}^{-1/2}\tilde{A}\tilde{D}^{-1/2}H^{(l)}W^{(l)}\right),$$

where $\tilde{A} = A + I$ is the adjacency matrix with added self-loops, $\tilde{D}$ is the corresponding degree matrix, $H^{(l)}$ represents the node features at layer l, $W^{(l)}$ is a trainable weight matrix, and σ denotes a non-linear activation function such as ReLU.

The final node embeddings are passed through a fully connected layer that predicts whether a user-business edge corresponds to a valid recommendation (label 1) or not (label 0). The model is trained using a binary cross-entropy loss function, optimized over both positive and negative samples.

By learning from both the structural connectivity and interaction patterns within the graph, the GNN is capable of capturing high-order correlations between users and businesses. This allows the system to generalize to unseen interactions and produce personalized, context-aware recommendations. Importantly, our model also integrates additional contextual signals—such as user sentiment, real-time weather conditions, and geolocation—further enhancing the relevance and precision of the suggested points of interest.

4.2.3 Categorizing Recommendation Items Using SVM

In our proposed recommendation system, the Support Vector Machine (SVM) plays a critical role in classifying the top-5 personalized business recommendations into appropriate semantic categories based on user-centric features. These recommendations are generated by considering multiple contextual factors, including the user's current sentiment (e.g., *happy*, *sad*, *neutral*), prevailing weather conditions (e.g., *sunny*, *rainy*, *mild*), and the geographical proximity between the user and the businesses. Each recommended business is described by quantitative attributes such as its rating (`stars`) and distance from the user (`distance_km`), which are used as input features for the SVM classifier.

The primary objective of incorporating SVM is to learn an effective decision function that can categorize each recommended business into one of several predefined semantic classes (e.g., *Parks*, *Museums*, *Shopping*, *Spas*). This classification step further organizes and refines the recommendations, enhancing user navigation and interpretability while enabling the system to generalize to new recommendations.

SVM operates by constructing a maximum-margin hyperplane in the feature space to separate data points of different categories. Let $\mathbf{x}_i = [x_{i1}, x_{i2}]^T$ denote the feature vector for business i, where x_{i1} corresponds to the rating and x_{i2} to the distance. Let $y_i \in \{1, 2, \ldots, K\}$ be the label indicating the business category. In the binary classification setting, the SVM optimization problem is formulated as:

$$\min_{\mathbf{w}, b} \frac{1}{2}\|\mathbf{w}\|^2$$

subject to the constraint:

$$y_i(\mathbf{w}^T \mathbf{x}_i + b) \geq 1, \quad \forall i,$$

where $\mathbf{w} \in \mathbb{R}^2$ is the weight vector perpendicular to the separating hyperplane, and b is the bias term. To classify a new instance $\mathbf{x}$, the SVM uses the decision function:

$$f(\mathbf{x}) = \mathbf{w}^T \mathbf{x} + b.$$

In the multi-class scenario applicable to our system, a One-vs-Rest (OvR) strategy is employed, where K binary classifiers are independently trained, each distinguishing one category from the others. The final predicted label $\hat{y}$ is determined by selecting the classifier with the highest decision score:

$$\hat{y} = \arg\max_k f_k(\mathbf{x}).$$

This formulation allows the system to learn the underlying relationship between business features and their semantic categories, independent of the contextual logic applied earlier (e.g., weather or sentiment rules). Consequently, it improves the robustness and scalability of the recommendation engine by enabling data-driven categorization and offering a more intelligent structuring of recommendations.

Algorithm 2: Hybrid Tourism Recommendation System

Data Collection

foreach *user with followers > 10K* **do**
 | `CollectInstagramData()`: scrape captions, hashtags, geotags, timestamps, metadata

Load Yelp business dataset (stars, location, categories)

foreach *user* **do**
 | `GetWeatherData(`*(user.location, user.timestamp)*`)`

Preprocessing

foreach *Instagram post* **do**
 | `PreprocessText(`*captions, hashtags*`)`

Sentiment Analysis with BERT

foreach *post* **do**
 | `ClassifySentimentBERT(`*(caption + hashtags)*`)` → sentiment label

foreach *user* **do**
 | Assign mood by majority vote over post sentiments

User Profile Construction

foreach *user* **do**
 | Store profile = {location, sentiment, weather, preferences}

GNN Recommendation Model

`ConstructBipartiteGraph()` using users, businesses, edges (positive + negative)

Initialize node embeddings

`TrainGNNModel()`

foreach *user* **do**
 | `RecommendPOIs()` → top-5 POIs

SVM Classification of POIs

Train SVM on {stars, distance} to predict category

foreach *recommended POI* **do**
 | `ClassifyBusinessWithSVM()` → business category

Final Recommendation Presentation

foreach *user* **do**
 | Group POIs by category and distance
 | Present grouped top-5 recommendations

4.3 Experiments

In this section, we present the datasets used and describe the recommendation process in detail.

4.3.1 Datasets

4.3.1.1 Data gathered from social network platforms

To build the Instagram dataset, We start the data collection procedure. Our target demographic is first determined to be public users with more than 100k followers. After that, we extract their

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profile details and over 200 posts, including hashtags, geolocation, and captions. Our 90-day data gathering period, which ran from August 1st to December 1st, 2023, included 10,000 posts written by 234 distinct Instagram users, all of whom had the potential to be influential. We used numerous Instagram accounts for login and ensured robust error handling while storing the data in JSON files.

4.3.1.2 Yelp Dataset

A Yelp dataset is a compilation of data gathered from the Yelp platform that includes user, business, and review information as well as other pertinent metadata. Research, analysis, and machine learning tasks frequently make use of these datasets. Details including company names, addresses, categories, review texts, ratings, user profiles, and more might be included. These datasets are useful for understanding trends across a range of businesses, sentiment analysis, recommendation systems, and consumer behavior research.

User information was obtained from an Instagram dataset, whereas the Yelp dataset was used to extract Points of Interest (POIs) across various global locations. The linkage between these two datasets is achieved using geographic coordinates, namely latitude and longitude

4.3.2 Experimental setup

4.3.3 Experimentation of BERT Model

For emotion analysis, we have deployed the proposed model on an Intel Core i7 CPU running at 2.40 GHz with 8 GB of RAM and an IDE drive running Windows 10 64-bit. We make use of an Integrated Development Environment (IDE), which is designed specifically for Python programming, and the pre-existing Python libraries, including Numpy, Pandas, and scikit-learn in Python 3.8 on PyCharm Notebook. To prove the efficacy of the approach suggested in this section, testing is done. We will start by going over the model parameters and experimental datasets for this purpose, Yelp and Instagram data sources. In our work, the BERT model is implemented through Python programming and the usage of its tools, particularly Pycharm. Python's broad support for tasks involving machine learning and natural language processing has made it the preferred programming language.

4.3.4 Experimental Recommendation Model

To comprehensively assess the performance of the MGat-Rec system, we conducted extensive experiments using widely accepted classification metrics—accuracy, precision, recall, and F1-score. These metrics were selected to maintain consistency with prior studies that utilized social media and Yelp datasets, thereby ensuring a reliable and meaningful comparison with existing state-of-the-art models. The dataset was partitioned into training and testing subsets following a 70-30 split, ensuring an even distribution of positive and negative samples. The model was trained for 50 epochs, employing a `GCNConv` layer to facilitate message passing and feature aggregation within the user-item interaction graph. Initial node embeddings for both users and businesses were generated through learnable embedding layers and subsequently refined using graph convolutional operations followed by ReLU activations.

The proposed GNN model delivered impressive performance, achieving an accuracy of 0.96, precision of 0.93, recall of 0.98, and an F1-score of 0.96. These results highlight the model's effectiveness in accurately identifying meaningful user-business interactions, while minimizing both false positives and false negatives. Notably, the high recall value indicates the model's capability to capture a large proportion of true positive recommendations, enhancing its reliability in delivering personalized content. Overall, the findings underscore the advantages of leveraging graph-based representations in recommendation systems. By modeling intricate relationships and enabling the propagation of contextual information—such as user sentiment and weather conditions—across the graph, the MGat-Rec framework significantly enhances recommendation accuracy and relevance.

To further validate our approach, we compared its performance with several established models, including RNN, LSTM, KNN, and XGBoost. (1) Recurrent Neural Networks (RNNs) and their advanced variant (2) Long Short-Term Memory (LSTM) networks are particularly effective in review-based recommender systems, as they excel at modeling sequential dependencies. These models analyze the temporal and emotional flow of user reviews, extracting deeper insights into user preferences and item characteristics, which results in more context-aware recommendations [101]. (3) The K-Nearest Neighbors (KNN) algorithm identifies patterns in user behavior—such as browsing history and clickstream data—to find items that resemble previously liked content, enabling the system to predict future interests and deliver relevant suggestions [147]. (4) XG-Boost, a high-performance gradient boosting framework, improves recommendation accuracy by iteratively correcting prediction errors through an ensemble of decision trees. This allows it to capture complex and non-linear user-item relationships, producing precise and data-driven recommendations [129].

4.3.4.1 Comparison with Other Models

A comprehensive comparison was conducted among six recommendation algorithms from both deep learning and machine learning paradigms: GNN, LSTM, RNN, KNN, Random Forest (RF), and XGBoost. This evaluation was based on four essential performance indicators: Accuracy, Precision, Recall, and F1 Score. Among the tested models, the Graph Neural Network (GNN) consistently delivered the most outstanding performance. It recorded the highest accuracy (0.96) and recall (0.98), reflecting its exceptional capability to model intricate user-item relationships and accurately identify relevant recommendations while minimizing false negatives. The GNN's ability to exploit graph structures and propagate contextual information plays a key role in this superior outcome.

The Long Short-Term Memory (LSTM) network also exhibited strong performance, particularly excelling in precision (0.97) and F1 score (0.94). This suggests that LSTM is highly effective in learning sequential and temporal dependencies in user behavior. Although its recall (0.91) was slightly lower than GNN's, LSTM remained highly competitive overall. The K-Nearest Neighbors (KNN) algorithm achieved moderate results, with scores around 0.87 across all metrics, making it a practical yet straightforward option for recommendation tasks. Random Forest (RF) performed slightly better than KNN, especially in accuracy (0.91) and F1 score (0.90), demonstrating that ensemble-based approaches can model more complex interactions without relying on deep learning architectures.

On the lower end of the performance spectrum, Recurrent Neural Networks (RNN) struggled with an accuracy of 0.67 and a precision of 0.64, suggesting difficulties in capturing long-term dependencies and adapting to more complex recommendation scenarios. XGBoost surpassed RNN

but still lagged behind the leading models, attaining an accuracy of 0.86 and F1 score of 0.84. While XGBoost remains a strong contender in structured data problems, it may underperform in recommendation systems unless paired with extensive feature engineering.

In conclusion, GNN proved to be the most effective model for recommendation tasks where relational data and contextual signals are essential. LSTM was also a high-performing model, particularly suited for capturing dynamic user behavior over time. KNN offered a balanced trade-off between simplicity and reliability, while RNN and XGBoost demonstrated limitations in this specific application domain. These findings reinforce the value of advanced neural architectures—especially GNNs and LSTMs—in building adaptive and intelligent recommendation systems.

The experimental outcomes for all models are presented in Table 4.3, from which several key observations can be drawn.

TABLE 4.3: Comparison of Recommendation Algorithms

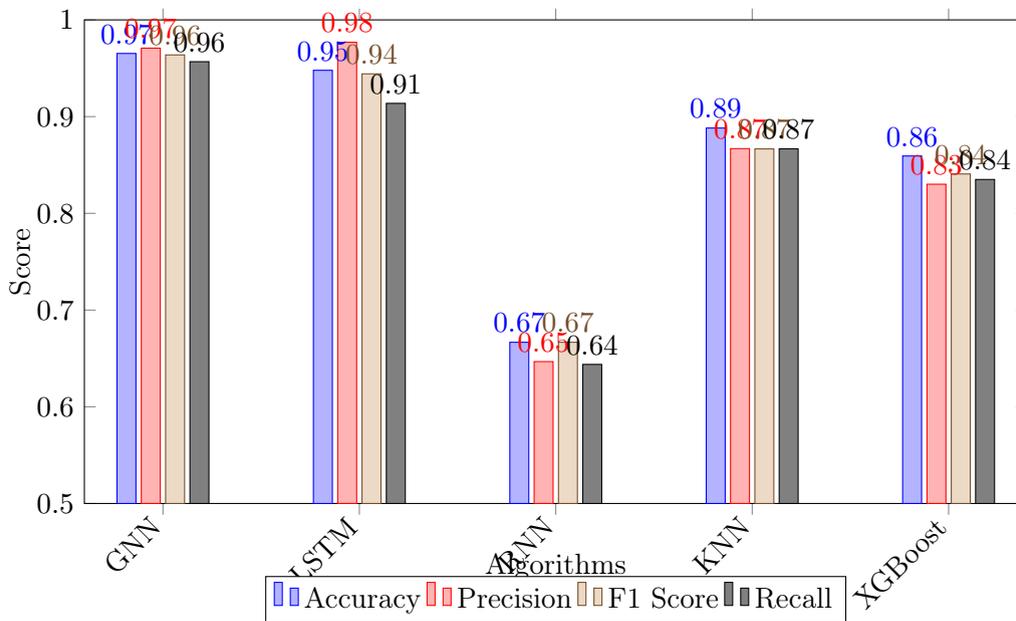| Algorithm	Accuracy	Precision	F1 Score	Recall
GNN	0.9653	0.9708	0.9638	0.9568
LSTM	0.9479	0.9769	0.9442	0.9137
RNN	0.6667	0.6467	0.6667	0.6438
KNN	0.8882	0.8669	0.8666	0.8667
XGBoost	0.8593	0.8301	0.8407	0.8350

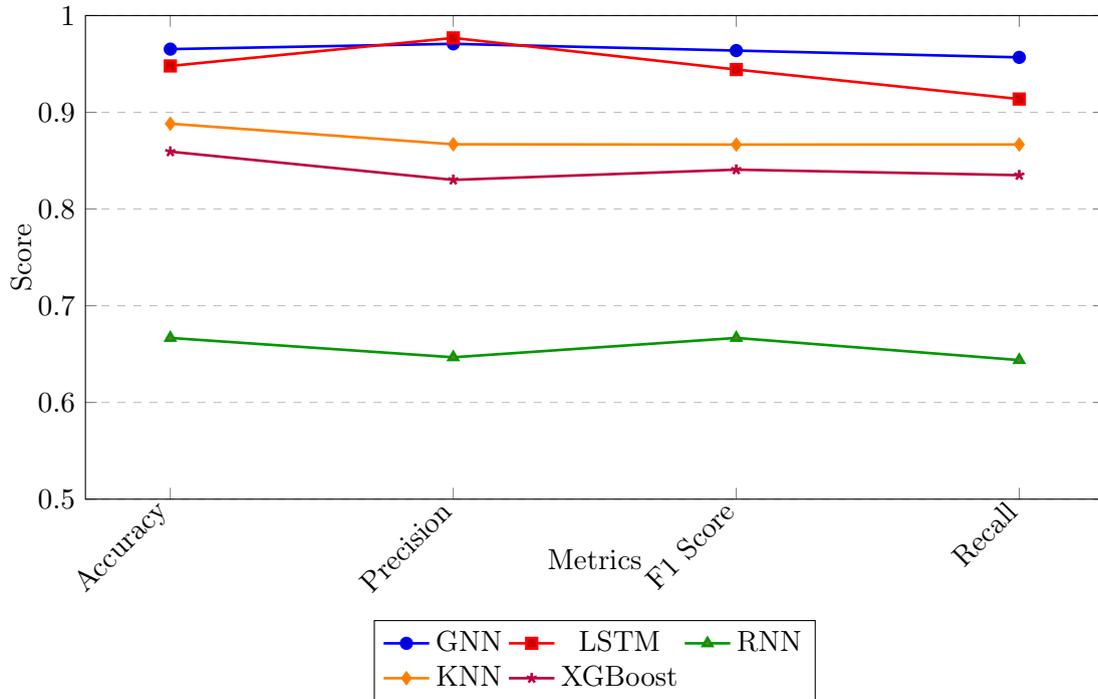FIGURE 4.10: Performance Comparison of Recommendation Algorithms

FIGURE 4.11: Comparison of Recommendation Algorithms using Accuracy, Precision, F1 Score, and Recall

The evaluation results clearly underscore the superior performance of the GNN model, which outperforms all other methods across the primary evaluation metrics: accuracy (0.9653), precision (0.9708), F1 score (0.9638), and recall (0.9568). These findings validate GNN's ability to effectively capture complex user-item relationships by utilizing the inherent structural features of graph-based data. The LSTM model also achieves strong results, particularly excelling in precision (0.9769), demonstrating its effectiveness in producing highly relevant recommendations by modeling temporal patterns in user behavior. However, its slightly lower recall (0.9137) compared to GNN indicates that it may occasionally overlook relevant items. The KNN algorithm delivers steady and well-balanced performance across all metrics, showcasing its reliability and simplicity, though it lacks the capacity to learn deeper patterns present in more dynamic recommendation tasks. XGBoost shows moderate effectiveness, limited by its inability to model sequential or graph-structured data, which affects its recall and overall F1 score. On the other hand, the RNN model exhibits the weakest results in all metrics, likely due to its challenges in learning long-term dependencies and vulnerability to vanishing gradient issues. Overall, GNN emerges as the most capable model for delivering personalized recommendations, offering a balanced combination of accuracy and comprehensiveness. LSTM remains a competitive choice for scenarios requiring sequence modeling, while simpler models like KNN and XGBoost may still be suitable for less complex recommendation settings.

4.3.4.2 Comparison with Other State-of-the-Art Methods

Tables 4.4 and 4.5 provide a comparative assessment of our proposed approach against leading state-of-the-art methods on a social media dataset. While our method does not always yield the highest accuracy scores, it consistently delivers robust and dependable results, underscoring its practical effectiveness within the tested scenarios. In contrast to conventional methods that often

operate within narrow confines, our system employs a comprehensive and integrative strategy to personalize the user experience.

By synthesizing a wide range of data inputs—including user profiles, individual preferences, geographical location, live weather updates, and Instagram usage patterns—our approach generates context-aware recommendations aligned with the user's present state. The filtering process, which considers location, emotional sentiment, and activity preferences, ensures that recommendations are both timely and relevant. Furthermore, the inclusion of weather-sensitive filtering greatly enhances the contextual appropriateness of the suggested activities. To maintain recommendation quality, Yelp ratings are incorporated to prioritize high-rated businesses.

What differentiates our system is its multi-faceted personalization architecture, which not only improves predictive accuracy but also boosts user engagement and satisfaction. In contrast, many current state-of-the-art techniques are constrained by their limited ability to utilize such rich contextual and environmental information, reducing their effectiveness in dynamic, real-world scenarios.

In our empirical evaluation, we assess the performance of the proposed system using two cut-off thresholds: Top@10 and Top@20. These evaluations are carried out on three social media datasets, employing four widely accepted performance metrics: Recall@10, Recall@20, nDCG@10, and nDCG@20. We benchmark our model's performance against a set of baseline methods, with the complete experimental results detailed in Tables 4.4 and 4.5.

TABLE 4.4: Comparative study of the proposed system with state-of-the-art methods using the social media dataset.

System	Dataset	Accuracy	Precision	F1 Score	Recall	RMSE	MAE
MGat-Rec	Instgram	0.9653	0.9708	0.9638	0.9568	0.1858	0.0535
BERT-SeqHybrid [209]	Flickr	0.6700	0.4000	0.5300	0.7900	0.0900	–
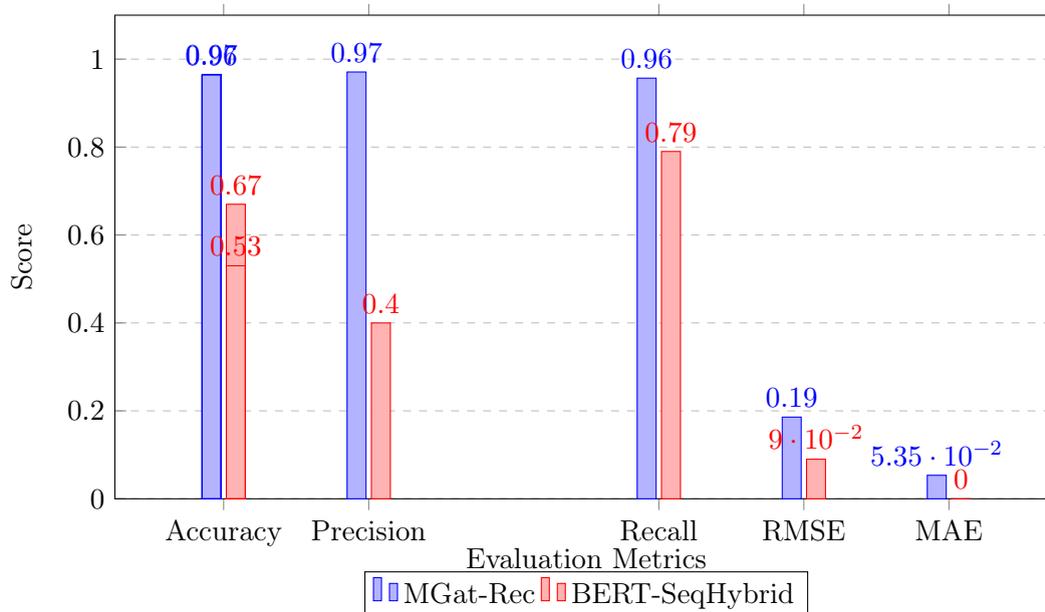
FIGURE 4.12: Comparison of Our Proposed System with BERT-SeqHybrid on Multiple Evaluation Metrics
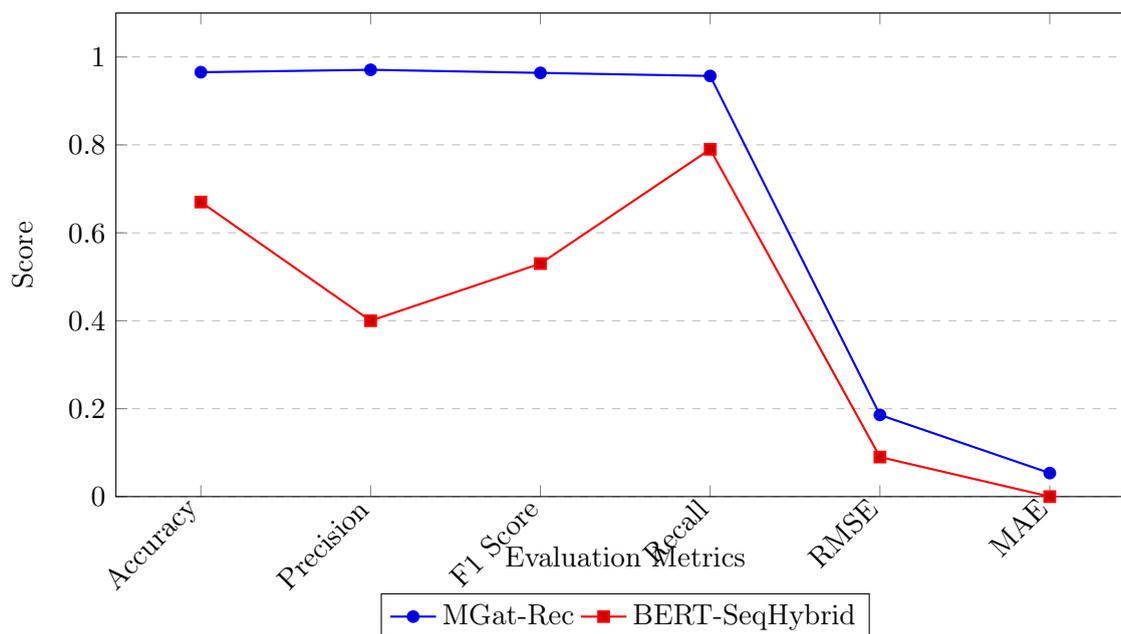
FIGURE 4.13: Performance Comparison Between Our System and BERT-SeqHybrid

TABLE 4.5: Comparative study of the proposed system with state-of-the-art methods using the social media dataset.

System	Dataset	NDCG@10	NDCG@20	Recall@10	Recall@20
MGat-Rec	Instagram	0.6054	0.6058	0.6054	0.6058
NCF [105]	Tourism	0.0367	0.0367	0.0288	0.0267

System	Dataset	NDCG@10	NDCG@20	Recall@10	Recall@20
GCNs-CF [215]	Tourism	–	0.1136	0.1294	0.1092
RetaGNN [115]	Instagram	0.0703	0.0673	–	–
SASRec [132]	Amazon	0.3219	–	–	–
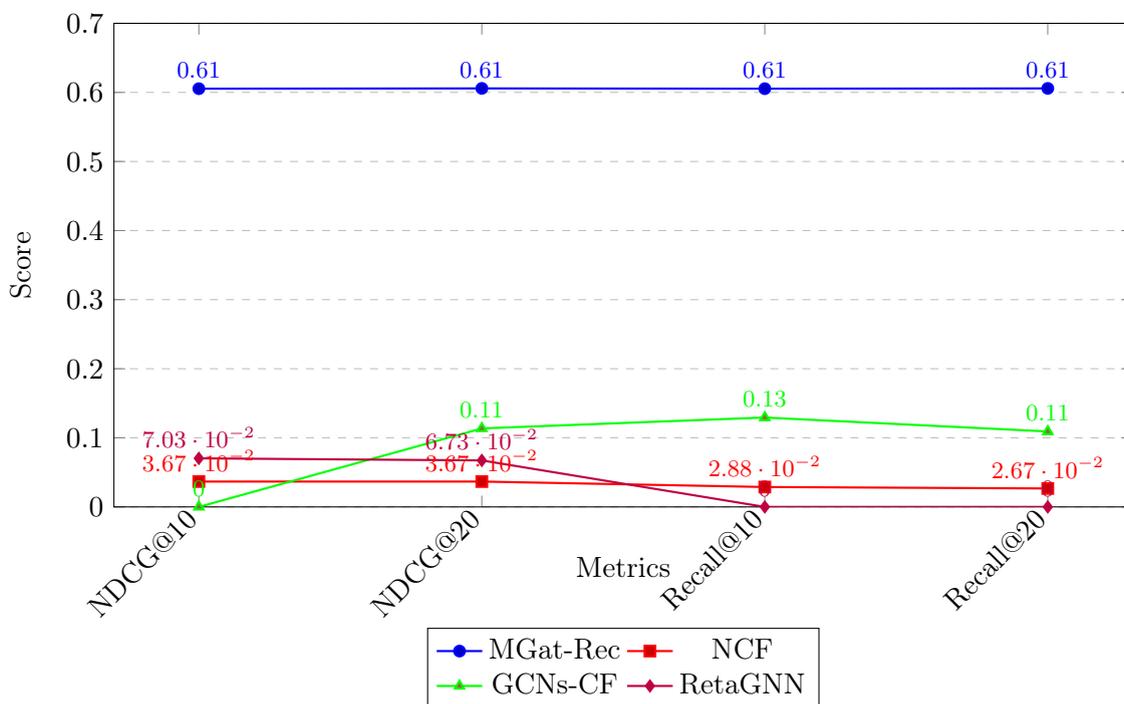
FIGURE 4.14: Comparison of NDCG and Recall Metrics Across Models
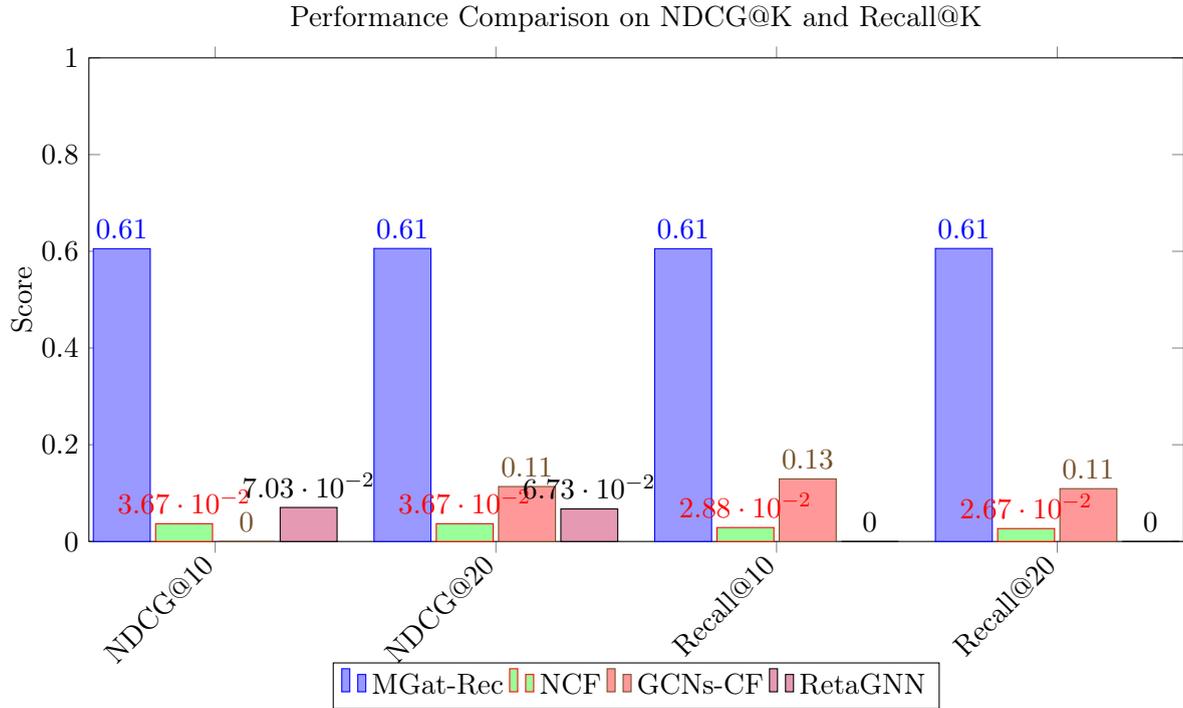
FIGURE 4.15: Performance comparison of the proposed system with baseline methods using NDCG@K and Recall@K metrics

4.3.5 Discussion

The evaluation results based on NDCG@K and Recall@K metrics offer compelling evidence of the proposed recommendation system's effectiveness. The MGat-Rec model achieves remarkably high performance, with NDCG@10 and NDCG@20 scores of 0.6054 and 0.6058, respectively, and identical values for Recall@10 and Recall@20. This consistent strength across both ranking precision (NDCG) and retrieval effectiveness (Recall) indicates that the system not only identifies relevant items with high accuracy but also retrieves a considerable proportion of them.

In comparison, baseline models such as Neural Collaborative Filtering (NCF) perform significantly worse, with NDCG limited to just 0.0367 and Recall scores below 0.03. This stark performance gap highlights NCF's inadequacy in modeling complex user-item relationships. Although GCNs-CF performs slightly better than NCF in terms of recall—achieving 0.1294 at Recall@10 and 0.1092 at Recall@20—it remains considerably weaker in ranking quality, especially in the top positions where relevance is most impactful.

Furthermore, despite being a graph-based approach designed for social recommendation tasks, RetaGNN shows only moderate results in this context, with NDCG scores of 0.0703 and 0.0673 for Top@10 and Top@20, respectively, and recall metrics not reported. These findings suggest that RetaGNN may not be well-optimized for the Instagram dataset or lacks the adaptability needed for this particular application.

Overall, the proposed MGat-Rec model exhibits consistent and superior performance across all evaluation criteria. Its ability to accurately rank and retrieve relevant items in Top-K recommendation scenarios positions it as a robust and promising solution for recommendation systems in social media environments.

4.3.6 Results

We present the results of the proposed system. Figures 4.16 and 4.17 shows User recommendations are divided into categories.
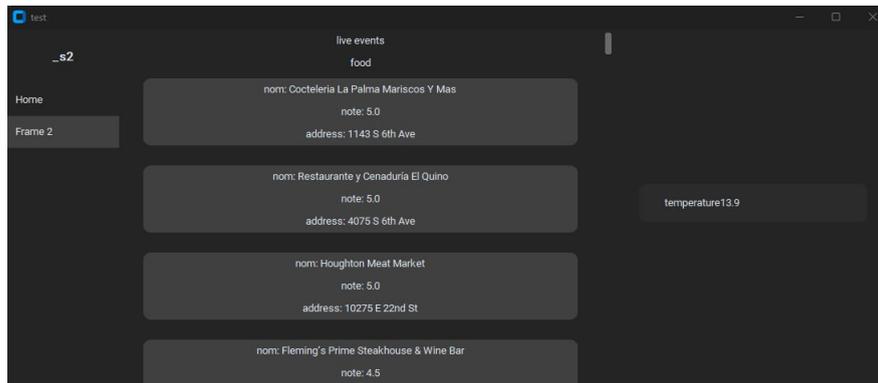
FIGURE 4.16: User recommendations divided into categories
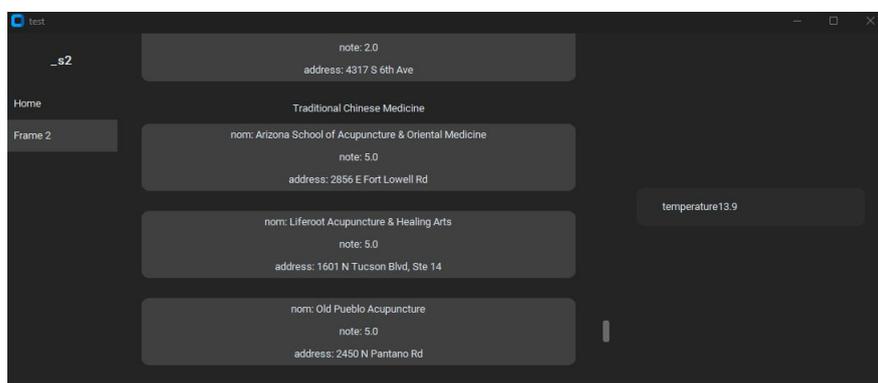
FIGURE 4.17: User recommendations divided into categories

Our proposed system presents a comprehensive solution for personalized Point of Interest (POI) recommendations by integrating user preferences, geographic location, mood, and real-time weather conditions. By incorporating contextual filtering based on sentiment and environmental factors, the system ensures that recommended activities are both relevant and timely. The integration of insights from Instagram and ratings from Yelp further enhances the accuracy and quality of suggestions. This approach significantly improves user satisfaction by aligning recommendations with individual needs and situational contexts, ultimately delivering personalized, context-aware experiences tailored to each user.

4.4 Conclusion

This chapter presents MGat-Rec, a novel multimodal graph-aware tourism recommender system that integrates emotional signals from Instagram with contextual and geographic data. By leveraging BERT for sentiment extraction and GNN for modeling complex user-POI relationships, the system delivers mood-aware, and context-sensitive recommendations. Our approach addresses the limitations of traditional models by unifying diverse data modalities into a dynamic and

adaptive framework. Overall, MGat-Rec enhances personalization in tourism, aligning recommendations with users' emotional states and situational contexts to improve engagement and satisfaction. Evaluation results highlighted MGat-Rec's outstanding performance, especially in NDCG@K and Recall@K, with notable gains in both accuracy and recall. The proposed system also surpasses other state-of-the-art techniques, which often rely on deep and hybrid models in complex recommendation scenarios. Overall, MGat-Rec advances the field by delivering context-sensitive, mood-aware recommendations tailored to modern travelers' dynamic needs. This underscores the adaptability and superior performance of our approach over methods constrained to methods that are limited to specific applications domains.

CONCLUSION AND PERSPECTIVES

Recommender systems (RS) provide users with information about various items based on their preferences, aiming to predict the most suitable options for them. These systems play a crucial role in suggesting relevant items within a vast and unfamiliar space that users would otherwise struggle to navigate. To achieve this, recommender systems focus on learning user preferences to identify relationship patterns. This information can be gathered explicitly through user ratings or implicitly by analyzing user behavior [190]. Recommender systems have been extensively implemented across various fields, including e-commerce, streaming services, social media, tourism, and healthcare.

Recommender systems are designed to filter and reduce the overwhelming volume of data available on social media, helping users find relevant content more efficiently. However, these systems encounter several challenges that can impact their effectiveness: (1) Lack of Relevant Data: Many recommendation models struggle with insufficient or low-quality data that fails to accurately reflect user preferences. This issue arises due to sparse user interactions, limited explicit feedback (such as ratings or reviews), and the dynamic nature of social media content. As a result, recommendations may not always align with users' actual needs and interests. (2) User disorientation: navigating vast amounts of information on social media can be overwhelming, especially when searching for specific topics. Without proper filtering and personalization, users may struggle to locate relevant content, leading to frustration, cognitive overload, and wasted time. This inefficiency prevents users from reaching their objectives effectively, as they may get lost in irrelevant or redundant information.

The main objectives of this thesis are threefold. First, it aims to enhance recommendation accuracy by integrating machine and deep learning methods with multi-criteria decision-making (MCDM) approaches, allowing the system to consider diverse factors such as price, quality, brand, and social influence while generating more relevant and personalized recommendations. Second, it seeks to design multimodal recommender systems capable of exploiting heterogeneous data, including user preferences, contextual information, emotional states, and social interactions. By leveraging these multimodal inputs and employing Graph Neural Networks (GNNs) for relational modeling, the system can generate adaptive and context-aware recommendations. Finally, this thesis introduces a multi-list recommendation mechanism that provides users with multiple suggestion lists tailored to different criteria (e.g., relevance, diversity, and context), thereby reducing user disorientation, enhancing personalization, and improving decision-making in various application domains.

Despite the improvements brought by our approach, there are several promising directions for future research:

- Large Language Models (LLMs) for personalized recommendations: recent advancements in LLMs, such as GPT-based models, offer new opportunities to enhance recommender systems. LLMs can analyze vast amounts of unstructured data, including user-generated content, reviews, and social media interactions, to better understand user preferences. Additionally, LLMs can improve conversational recommendation systems by engaging users in natural dialogue, refining recommendations dynamically based on contextual cues and nuanced user intents. Future research should explore how fine-tuned LLMs can be integrated into recommendation architectures to create more intelligent, adaptive, and human-like recommendation experiences.

- Contextual and Social-Aware Systems: Future systems should incorporate richer contextual signals such as social ties, mobility patterns, and environmental conditions to deliver more reliable and holistic recommendations.

By pursuing these directions, recommender systems can evolve from static predictors to adaptive, explainable, and user-centric companions that better support decision-making in complex digital environments.

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AUTHOR'S PUBLICATION

❖ International publications

❏ Chemlal, Maroua, Zedadra, Amina, Zedadra, Ouarda, Guerrieri, Antonio, & Kouahla Med Nadjib. (2024). A Multi-Criteria Food and Restaurant Recommendation System. Journal of Universal Computer Science, 30(12), 1724.

❏ Chemlal, Maroua, Zedadra, Amina, & Kouahla Med Nadjib. Multi-List Recommender System for Smart Tourism: A Deep Learning Approach Integrating Mood, Social, and Contextual Data, Current statue: Under review.

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❏ Chemlal, Maroua, Zedadra, Amina, & Kouahla, Med Nadjib. (2024). Tailored POIs Recommendations: A Machine Learning Approach to Personalized Experiences, The National Conference on Computational Engineering, Artificial Intelligence and Smart Systems- NCCEIASS2024, Tamanrasset, Algeria.