



**Dissertation Submitted to the Department Of Computer Science in Partial  
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**Recommender systems for multimodal transportation systems in  
smart cities**

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# بِسْمِ اللَّهِ الرَّحْمَنِ الرَّحِيمِ

*To my dear mother, who has always been my source of strength and without whom  
I would have achieved nothing,*

*To my late father, whom I hope to make proud with every step I take in my life,*

*For my husband Amine, who is a constant source of support at every step I take,*

*For my brother Boualem and my sister Ikram, my companions in life who walk  
beside me in every step of life,*

*For my grandfather and all my uncles and aunts who have shown me support as if I  
were their own daughter,*

*For my in-laws who have quickly become a second family,*

*I dedicate this humble work,*

*In the hope of making more contributions in the future, InshAllah.*

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## List of Abbreviations

**CB** Content based systems. 11, 14

**CF** Collaborative filtering systems. 11, 13, 14, 24

**HBF** Hybrid based filtering systems. 11, 13

**ICT** Information and communication technologies. 10, 15, 16

**MAE** Mean Absolute Error. 14, 15

**MTR** Multi-modal transportation recommendations. 28–30

**RMSE** Root Mean Squared Error. 14, 15

**RS** Recommendation Systems. 10, 11, 13–15, 24, 25

**SC** Smart Cities. 15–19

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# 1 Introduction

In today's urban environments, multimodal transportation systems play a vital role, particularly in cities where navigating from a point A to a point B involves utilizing various public transit modes. However, familiarizing oneself with all available transit options within a city can be intimidating, whether you're a visitor or a resident. This is why it's important to combine recommender systems with multimodal transport systems in the context of smart cities.

Recommendation systems won't just ensure finding a route by creating combinations of transportation, as people's preferences vary from one individual to another. For some, the focus is on cheaper travel, while for others, speed is paramount. Certain individuals aim to avoid specific modes of transportation while favoring others. Therefore, such systems will enable people to find these routes based on each user's personal preferences. Some systems may even surpass individuals' desires, while also aiding the flow of public transportation by distributing requests across multiple modes of transport, recommending transportation modes evenly during certain hours to avoid congestion for the benefit of transportation companies as well as customers.

From its inception, this study has captivated researchers, each offering their unique perspective and innovation to address existing problems. Initially conceived as a means to organize solutions, the focus soon shifted towards devising optimal systems for the largest cities. Subsequently, efforts were directed towards achieving superior outcomes in terms of user preferences, enhancing the city's transportation cycle, tailoring recommendations to specific locations, adapting to temporal circumstances, and even considering the timing of requests. Numerous initiatives have emerged, many of which have enjoyed tremendous success. However, this dynamic field continues to evolve, fostering further enrichment and innovation.

The objective of our report is to present a state-of-the-art overview of multimodal transport recommendation in smart cities. We begin with an introductory chapter covering the three pillars of this study: recommendation systems, smart cities, and multimodal transportation. Subsequently, we delve into the second chapter, where we discuss recent advancements in both recommendation systems and multimodal transport recommender proposed solutions. At the end, we provide a synthesis of the methods used in these recommendation systems.

## **First part: Background**

## 2 Background

In this section, we cover three main topics: recommendation systems, smart cities, and multi-modal transportation. Recommendation systems personalize user experiences, smart cities use Information and communication technologies (ICT) to optimize urban services, and multi-modal transportation integrates diverse transit modes for efficient mobility.

### 2.1 Recommendation Systems

Recommendation Systems (RS) have enjoyed success since their first appearance in the 1990s Adomavicius and Tuzhilin 2005. Despite the extensive work done to develop new approaches in RS, research has not waned. Every day, we witness the increasing indispensability of RS in our lives due to their involvement in various activities Iftikhar et al. 2023. In today’s world, where there is a vast array of choices across all domains ranging from choosing a restaurant to dine at, deciding on an activity to pursue, to selecting the best travel itinerary, RS provides invaluable support in making these decisions, thus reducing information overload Rodríguez-Hernández et al. 2015; Saini and Singh 2023. Therefore, each year sees improvements in the implementation of RS to achieve optimal results Saifudin and Widiyaningtyas 2024. Furthermore, even the current generation of RS requires further improvement to be more effective and applicable in broader domains of real life Adomavicius and Tuzhilin 2005.

#### 2.1.1 Definition

In its most common definition, a Recommender System is an algorithm that rates items, aiming to identify those with the highest ratings, as they are likely the ones preferred by the user. Following this, the system then suggests these top-rated items to the user. Adomavicius and Tuzhilin 2005; Saifudin and Widiyaningtyas 2024; Rodríguez-Hernández et al. 2015. Additionally, it’s important to mention that the method of rating varies among different RS. Each system employs its own unique approach to analyzing data sources in order to establish connections between users and items Melville and Sindhvani 2002.

#### 2.1.2 Types of Recommendations Systems

As the methods of generating recommendations vary from one system to another, RS are categorized into three main classes as shown in the figure 1 that describe the general approach: Collaborative Filtering, Content-based Filtering, and Hybrid filtering, which combines elements of both Adomavicius and Tuzhilin 2005; Rodríguez-Hernández et al. 2015; Melville and Sindhvani 2002.

**Content based systems (CB):** This method operates on the intuition that if a user liked a particular item, they'll probably like similar ones as well. It works by identifying similarities between items and then recommending those with features similar to those the user has previously favored Saifudin and Widiyaningtyas 2024; Rodríguez-Hernández et al. 2015. To ascertain the items the user favored previously, various methods are employed. These can be explicit, such as directly asking the user, or implicit, which involves analyzing user behavior Adomavicius and Tuzhilin 2005. In this approach, dealing with cold starts 2.1.3 is usually not an issue, as every item/user has its attributes/preferences defined once it's entered in the database. However, if there isn't a sufficient amount of information about the user's preferences, he'll receive fewer recommendations Saifudin and Widiyaningtyas 2024.

**Collaborative filtering systems (CF):** In this second approach, the RS suggests items to users based on ratings from others whose behaviors align closely with theirs Adomavicius and Tuzhilin 2005; Rodríguez-Hernández et al. 2015. This method stands out as the most popular and widely utilized one, with significant advancements in both academia and industry Adomavicius and Tuzhilin 2005. While this approach is widely used, it has both advantages and disadvantages. One advantage is that it doesn't require additional information about items or users when adding them to the database; rather, it relies on the interaction between users and items. However, if there isn't enough interaction, the system may generate fewer recommendations Saifudin and Widiyaningtyas 2024. Collaborative filtering systems, in turn, are divided into two general classes: Memory-based, which uses the database each time for recommendation, and Model-based, which constructs a model for predictions Breese, Heckerman, and Kadie 1998. Similar to the previous approach, the ratings can be either explicit or implicit Breese, Heckerman, and Kadie 1998.

**Hybrid based filtering systems (HBF):** Both of the instinctive approaches mentioned have their own set of advantages and disadvantages. To address the limitations of each while capitalizing on their strengths, hybrid collaborative systems were developed. These RS types combine elements of both collaborative filtering and content-based systems into a single structure Adomavicius and Tuzhilin 2005; Saifudin and Widiyaningtyas 2024; Rodríguez-Hernández et al. 2015. We have various methods available for constructing hybrid collaborative systems, which vary according to the data employed Saifudin and Widiyaningtyas 2024. These methodologies can be categorized into four main classes Adomavicius and Tuzhilin 2005:

1. Implementing collaborative and content-based methods independently, then combining their predictions.
2. Integrating specific content-based features into a collaborative approach.
3. Incorporating selected collaborative characteristics into a content-based approach.

4. Developing a comprehensive unified model that incorporates both content-based and collaborative attributes.

The article Adomavicius and Tuzhilin 2005 provides an extensive review of various approaches utilized in the construction of hybrid recommendation systems, drawing from a wide range of scholarly works.

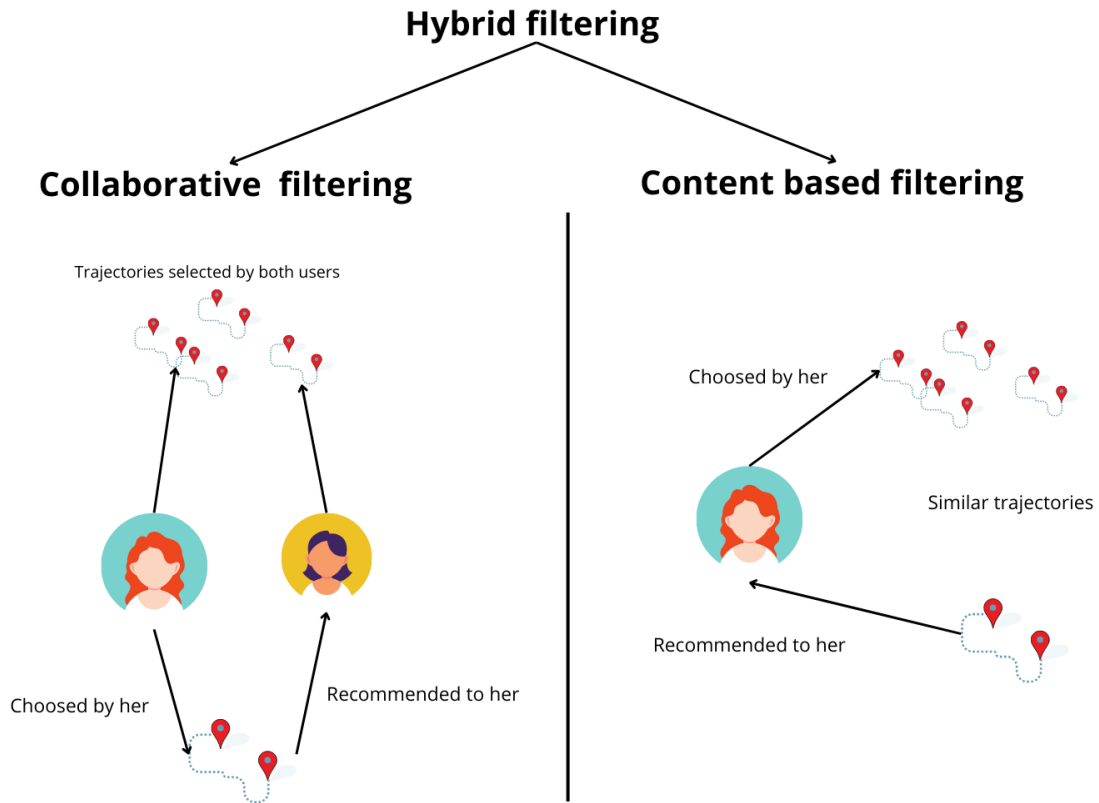


Figure 1: The three types of recommender systems: Collaborative Filtering, Content-Based Filtering, and Hybrid Systems

### 2.1.3 Challenges and Limitations

Recommender systems, like any other system, come with their own set of challenges and limitations. These challenges arise at various stages of the recommendation process, such as scalability during the recommendation process itself, difficulties in finding suitable datasets prior to recommendation, and issues related to fraud outside of the recommendation process Saifudin and Widiyaningtyas 2024. Let's take a brief overview of the most common limitations encountered.

**Cold start Problem:** One of the primary challenges faced by RS occurs when they encounter a lack of information or data absence when making predictions for new items or users Saifudin and Widiyaningtyas 2024. This issue is also referred to as the new-item problem or the first-rater problem Melville and Sindhvani 2002. While it is a concern across all types of RS, it poses a particularly significant challenge for collaborative filtering recommenders due to their reliance on historical ratings for recommendations.

**Sparsity Problem :** This problem arises when there's insufficient information available, as only a few items in the database are evaluated by the user. This results in sparse user-item matrices, making it challenging to find successful resemblances and provide effective recommendations Saifudin and Widiyaningtyas 2024; Melville and Sindhvani 2002. Additionally, data sparsity leads to coverage issues, where only a small percentage of items in the system can be used for recommendations Saifudin and Widiyaningtyas 2024. This poses challenges for collaborative filtering systems as it reduces the likelihood of finding similarity between users Melville and Sindhvani 2002. This problem often occurs when there's a high ratio of items to users or during the initial stages of system use. To address this issue, additional information about the topic can be considered, or assumptions can be made about how the data was created. These steps help improve the accuracy of filling in missing information Melville and Sindhvani 2002.

**Scalability Problem :** Scalability poses a significant challenge for many recommendation systems Saini and Singh 2023, especially as the number of users and items grows Saifudin and Widiyaningtyas 2024. Efficiently producing recommendations becomes increasingly difficult with this expansion. While developing a filtering system that can scale effectively requires careful consideration Saini and Singh 2023, there are dimension reduction techniques available to address scalability issues and accelerate recommendation processes, such as Singular Value Decomposition Saifudin and Widiyaningtyas 2024.

**Running Time Problem:** Enhancing efficiency is a crucial focus of every research endeavor. As indicated in Saifudin and Widiyaningtyas 2024, employing algorithms abbreviated as CF and HBF introduces modifications that can significantly accelerate processing times compared to earlier approaches.

**Accuracy Problem:** It's one of the most common challenges faced by recommendation system algorithms, each of which endeavors to enhance accuracy through various research methods. The ongoing efforts to improve the accuracy of RS are both continuous and exciting Saifudin and Widiyaningtyas 2024.

**Fraud Problem:** The fraud problem, while less technical compared to others, remains a significant concern in RS. Sellers, for example, may manipulate RS to benefit from recommendations, often seen in commercial systems where they aim to lower the average ratings of competitors while boosting their own. CB methods are less susceptible to this issue as they are not reliant on ratings. However, CF methods often face challenges in dealing with this manipulation Melville and Sindhvani 2002.

The article Saifudin and Widiyaningtyas 2024 provides a ranking of the frequency of the issues discussed in the RS across various systems.

#### 2.1.4 Evaluating Recommender System Performance

To properly assess our RS, evaluation is essential. We can gauge its effectiveness by comparing its recommendations to a predefined set of user ratings Melville and Sindhvani 2002. The article Saifudin and Widiyaningtyas 2024 outlines six key metrics commonly used for this purpose, such as :

- Root Mean Squared Error (RMSE) :

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (1)$$

- Mean Absolute Error (MAE) :

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (2)$$

where :

- $\hat{y}_i$  : is the predicted value.
- $y_i$  : is the actual value.
- $n$  : is the number of observations.

- Weighted Precision : Measures the proportion of true positives among the items predicted as positives, considering class weights. Useful for imbalanced classes.

**Formula:**

$$\text{Weighted Precision} = \frac{\sum_{i=1}^k \text{Precision}_i \cdot n_i}{\sum_{i=1}^k n_i}$$

- Recall : Measures the proportion of true positives among all actual positives. Indicates the model's ability to detect true positives.

**Formula:**

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

- **Weighted F1 Score** : The harmonic mean of weighted precision and recall, considering class weights. Balances precision and recall for imbalanced data.

$$\text{Weighted F1 Score} = \frac{2 \cdot \text{Weighted Precision} \cdot \text{Weighted Recall}}{\text{Weighted Precision} + \text{Weighted Recall}}$$

- **Mean Reciprocal Rank (MRR)** : Measures search/recommendation effectiveness, averaged over the reciprocal ranks of the first relevant results. Useful for ranking tasks.

**Formula:**

$$\text{MRR} = \frac{1}{|Q|} \sum_{i=1}^{|Q|} \frac{1}{\text{rank}_i}$$

- **AUC-ROC (Area Under the Receiver Operating Characteristic Curve)** : Evaluates binary classification performance by measuring the area under the ROC curve, plotting true positive rate against false positive rate.

**Formula:** AUC is typically calculated using numerical integration methods.

And others like Normalized Discounted Cumulative Gain (NDCG). Interestingly, RMSE and MAE seem to be the most frequently used, suggesting their comparable nature. However, it's worth noting that neither metric has a solid theoretical justification, often leading to a choice based on practical considerations Saifudin and Widiyaningtyas 2024.

### 2.1.5 Multicriteria Ratings

When discussing predictions made by RS, we often think about categorizing items based on single criteria, like taste for food or interest for books, which are examples of single-rating RS. However, in our daily lives, we often encounter situations where multiple factors need to be considered, not just one. In the article Adomavicius and Tuzhilin 2005, various solutions have been proposed, including finding Pareto optimal solutions, using a linear combination of criteria, optimizing the most important criterion, and successive optimizations of individual criteria. Despite being an intriguing subject in RS, there hasn't been extensive research in the recommender systems literature Adomavicius and Tuzhilin 2005, indicating a need for further exploration in this area.

## 2.2 Smart cities

Smart Cities (SC) represent a major evolution in urban management, integrating ICT to improve citizens' quality of life. This section explores the definition of smart cities, their key

technologies, their challenges, and provides some recommendations.

### 2.2.1 Definition

The term "Smart cities" was first introduced in a book published in the United States in 1992, underscoring the increasing adoption of ICT in contemporary urban infrastructures. However, its significance extends beyond technological innovation; it involves the utilization of various sensors, actuators, cameras, and devices within vehicles, buildings, or houses to monitor their physical structure and integrate with other related applications, while also considering human values alongside technological advancements Nguyen, Nawara, and Kashef 2024. Despite numerous attempts to clarify its meaning, a universally agreed-upon definition remains difficult to define Lai and Cole 2022. Additionally, we find multiple approaches to building a SC Nguyen, Nawara, and Kashef 2024, with variations depending on regional contexts Lai and Cole 2022.

### 2.2.2 Key Technologies

SC rely on essential technologies that form the fundamental framework for their operations in the modern world. These technologies enable connectivity, data collection, and smart decision-making processes, serving as the backbone of urban development. And together they drive the development of SC, making them more sustainable, resilient, and responsive to citizens needs. Among these key technologies we find the following :

- The Internet of Things : refers to the process of connecting physical objects to the internet or other network protocols. These objects are equipped with sensors, processing units, and software, enabling them to interact with other devices and systems by accessing, exchanging, and processing data. The collected data is stored in databases for processing, allowing administrators to track the city's progress and make informed decisions regarding the planning, control, and coordination of devices and systems Nguyen, Nawara, and Kashef 2024.
- Big Data : SC generate massive volumes of data from diverse sources, making the role of big data management crucial. The "5 V's" of big data—Volume, Variety, Velocity, Veracity, and Value—underscore the complexities and potentials linked with handling extensive and varied datasets Nguyen, Nawara, and Kashef 2024.
- Cloud computing : Cloud computing, encompassing the provision of computing services such as servers, storage, databases, networking, software, and analytics over the internet, facilitates rapid innovation, flexibility in resource allocation, and economies of scale. By embracing cloud-based applications, SC can alleviate the burden of maintaining internal databases or physical servers. Cloud providers like Amazon, Microsoft, or Google

offer services and resources that are accessible and shareable across multiple devices simultaneously, thereby streamlining data management and enhancing scalability for SC administrators Nguyen, Nawara, and Kashef 2024.

- **Blockchain** : Blockchain, with its decentralized and immutable ledger system, plays a pivotal role in SC . By safeguarding transactions from alteration or control by any single entity, blockchain ensures security and integrity. This technology enhances the efficiency and transparency of urban governance by facilitating secure data sharing among city departments and simplifying processes such as permitting and procurement through the implementation of smart contracts. Furthermore, blockchain encourages the development of creative citizen engagement initiatives. Ultimately, blockchain holds the promise of transforming smart cities into more resilient, inclusive, and sustainable urban environments Nguyen, Nawara, and Kashef 2024.
- **Machine learning** : Machine learning involves the use of algorithms and statistical models to enable SC applications, such as data analytics, sensor information fusion, anomaly detection, and emotion recognition. It plays a crucial role in optimizing SC operations, leading to enhanced efficiency, effectiveness, and overall performance Fadhel et al. 2024.

### 2.2.3 Challenges

SC use advanced technology to address various challenges such as traffic congestion, environmental pollution, and energy efficiency. However, in this process, they encounter many challenges, including the following:

- **Smart Sensors in Smart Cities**: Sensors are vital components in the creation of SC, as they measure the physical attributes of devices and enable diverse functionalities. However, integrating sensors into SC infrastructure encounters challenges such as safety and security management, privacy issues, and energy constraints in wireless network sensors Nguyen, Nawara, and Kashef 2024.
- **Security and Privacy**: SC gather lots of data, including details about citizens, which needs to be kept safe from unauthorized access or tampering. However, this data can be at risk of cybercrime as it moves through different stages. Challenges include preventing unauthorized access to stored data and ensuring data streams are not disrupted during transmission. It's important to protect citizens private information Nguyen, Nawara, and Kashef 2024.
- **The cost of SC** : The cost of implementing SC is a significant concern, affecting both the initial development expenses and ongoing operational costs. Development costs encompass the implementation of SC initiatives, including planning strategies to meet citizens

needs and installing various devices, sensors, and software, which can be both time-consuming and expensive. Operational costs relate to the ongoing maintenance needed to ensure SC operate efficiently throughout their lifespan. It's crucial to allocate sufficient resources to maintain smart facilities and ensure uninterrupted benefits for citizens Nguyen, Nawara, and Kashef 2024.

- **Data extraction and management** : Data extraction from various sources, alongside the management of urban data, presents labor-intensive tasks, particularly due to the diverse sources and complex data types involved. These challenges underscore the essentiality of implementing efficient data management strategies to support the development of SC Fadhel et al. 2024.
- **Energy consumption** : the challenge of energy consumption in IoT systems remains pertinent. These systems, integral to the functioning of SC, involve the collection, analysis, and transmission of large quantities of data. This process, essential for various SC functionalities, demands considerable resources such as storage capacity, cloud computing, and wide bandwidth, leading to significant energy consumption. Additionally, the energy needs of the sensing devices used in SC infrastructure further contribute to this challenge Omrany et al. 2024.
- **Scalability, adaptability, and reliability** : another significant challenge in the development of SC. These systems must seamlessly adjust to evolving user demands, incorporate new services and devices, and maintain consistent performance. Additionally, they need to evolve to meet the dynamic requirements of SC, accommodating a diverse range of devices with varying capabilities, all while ensuring the robustness and reliability of IoT systems to deliver high-quality service despite scaling up to integrate more devices and services Omrany et al. 2024.
- **Ethical concerns** : Ethical considerations in IoT applications for SC involve a range of challenges such as intellectual property rights and data privacy. Five primary issues have been identified in this context: informed consent, privacy, information security, physical safety, and trust Omrany et al. 2024.

#### **2.2.4 Recommendation**

To address the many challenges of SC, several strategies can be put in place. Article Fadhel et al. 2024 offers various recommendations to make the functioning of smart cities more efficient. Here are some of them:

- Utilizing a machine learning-driven intrusion detection system to bolster communication security within mobile cloud computing environments.

- Utilizing supervised machine learning methods to harmonize diverse data sources, enhancing decision-making efficacy in urban planning.
- Proposing the adoption of location-based filtering and global descriptor similarity-based ranking methods for recognition tasks to enhance recognition outcomes, surpassing the effectiveness of local descriptor-based re-ranking approaches.
- Taking into account spatial-temporal correlations among various local regions within a city to attain precise prediction results, leading to a deeper understanding of urban dynamics and enhancing prediction accuracy and reliability.
- Implementing advanced techniques such as dual-attention deep reinforcement learning, lifelong learning, and multi-granularity fusion methods in IIoT environments to optimize resource utilization, system performance, and accuracy.
- Suggesting the implementation of explainable recommender systems to increase user acceptance rates by providing clear explanations for energy-saving actions. This strategy aids in reducing energy wastage and promoting sustainability initiatives.

### **2.3 Multi-modal transportation**

In the realm of SC, transportation has experienced a significant revolution. Whether it's in private vehicles with systems for selecting optimal routes or finding available parking spaces, or in public transportation, be it unimodal or multimodal as shown in the figure 2, where options range from selecting the most appropriate mode of transport to identifying stops with minimal crowds or the closest proximity. These advancements continue to evolve due to the numerous technologies and advantages facilitated by SC initiatives.

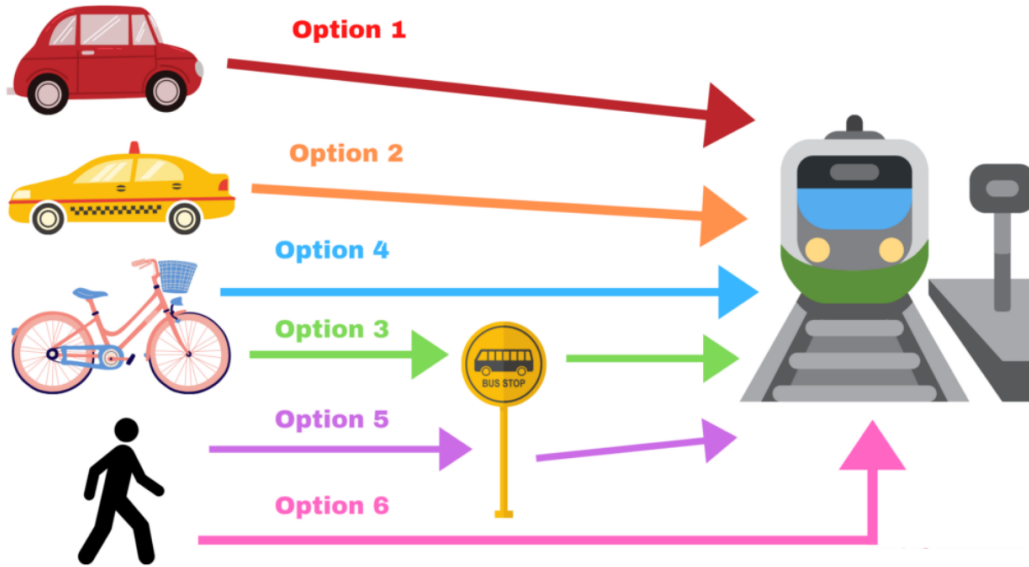


Figure 2: Multimodal transportation

### 2.3.1 Definition

The evolution of multimodal transportation systems is a key indicator of the advancement of smart transportation. These systems are defined in various ways, such as "the shipment of cargo and the movement of people involving more than one mode of transport during a single seamless journey," or "movement in which two or different transport modes are linked end to end in order to move freight and/or people from point of origin to point of destination." Another definition is "the combination of modes, usually ship, truck, or rail, to transport freight." Dua and Sinha 2015 All these definitions simply refer to systems that use a combination of different transportation methods to travel from a starting point to a destination.

### 2.3.2 Transition from Conventional to Multimodal Transportation Planning

Transitioning to a multimodal transportation approach involves addressing various issues and adapting organizational structures to support diverse transportation modes. Conventional planning primarily focuses on automobile travel, promoting high vehicle ownership and low land-use density, while often neglecting broader impacts such as public health and environmental concerns. This approach uses models designed for highway evaluation, emphasizing speed and congestion reduction. In contrast, multimodal planning integrates various transportation modes, encouraging higher land-use density and mixed-use development. It values modal diversity and social equity, requiring more complex analysis tools to assess the quality and interconnectivity of different transportation modes. Effective organizational structures are crucial for

coordinating efforts and achieving stability. Most State Departments of Transportation (DOTs) use a divisional structure to manage functions by transportation mode. To incorporate multimodal approaches, these structures must evolve, considering non-highway modes alongside traditional highway functions. This evolution requires reengineered processes, skilled staffing, and advanced analytical tools Smith 2013.

### **2.3.3 Best Practices in Multimodal Transportation Planning**

The evolution of multimodal transportation planning has led states to adopt best practices that emphasize equitable consideration of various transportation modes, organizational restructuring, and enhanced public involvement. Successful approaches include fostering strong modal advocacy within departments and implementing flexible funding mechanisms. States have also improved methods for assessing transportation needs and selecting projects, with a focus on integrating different modes through simultaneous analysis and advanced planning models. Public involvement is crucial, with efforts to engage stakeholders and users of the transportation system, ensuring their input shapes the planning process. Additionally, the use of performance measures, such as accessibility, travel time reduction, and multimodal options, helps evaluate the effectiveness of transportation systems and supports data-driven decision-making. These comprehensive strategies underscore the importance of evolving organizational structures and enhancing coordination to achieve an efficient and interconnected multimodal transportation network Smith 2013.

### **2.3.4 Challenges**

Statewide multimodal transportation planning faces several key challenges. First, there is a growing need for performance-based planning, where transportation agencies are accountable for measurable results, not just outputs. This requires developing neutral performance measures using readily available data. Second, greater public and stakeholder involvement is essential, ensuring that diverse interests, including minority and low-income populations, are fairly represented. Another major challenge is integrating advanced technology, which can revolutionize data processing and analysis but needs better tools and methods. Environmental sustainability and fair distribution of transportation benefits are also becoming important. Additionally, coordinating planning efforts across local, regional, and multistate levels is crucial to avoid political gridlock and ensure comprehensive solutions. Finally, recruiting, training, and retaining skilled professionals with the necessary technical expertise remains a significant hurdle. Pedersen Chairman: Neil J. Pedersen

In conclusion, recommendation systems, smart cities leveraging ICT, and multi-modal transportation contribute crucially to shaping modern urban environments, offering enhanced

decision-making, sustainable service optimization, and efficient mobility solutions, respectively, towards smarter cities for the future.

## **Second part: State of the art**

### 3 State of the art

In the modern context of smart cities, there is a wide array of approaches to developing recommendation systems. Notably, this innovation has extended into the domain of multimodal transportation recommendation systems. Consequently, this section aims to explore some of the latest advancements in this field.

#### 3.1 Related work in Recommendation Systems

As previously noted, RS have been a focal point of interest since their inception, and to this day, significant efforts continue to be devoted to enhancing their performance. In this overview, we will highlight some of the recent initiatives aimed at improving RS.

**In Khelloufi et al. 2024**, the authors presents an advanced service RS customized for the Social Internet of Things landscape. The system design includes various stages, starting with system modeling, where the architectural design and data flow of the recommendation framework are outlined. SIoT objects are represented as tuples, and their relationships are depicted in a graph, addressing challenges like the service explosion problem. The importance of semantic relationships between multimodal items is emphasized, leading to the creation of modality-aware kNN item graphs for accurate representations. The system leverages processed information to tailor recommendations based on user preferences, highlighting the SIoT's capability for smooth service coordination. Further, a novel kNN modality-aware graph construction technique is introduced, leveraging multimodal data to enhance recommendation accuracy by considering semantic relationships between items. Multimodal latent graph aggregation consolidates information from various modalities to generate comprehensive recommendations, considering user preferences for specific modalities. Additionally, a scenario case study demonstrates the practical application of the RS in a multimodal data-rich SIoT environment across various domains. Experimental evaluations using comprehensive Amazon datasets assess the proposed model's performance, showcasing its efficacy in mitigating the cold-start problem and providing accurate recommendations even with limited historical data. The study underscores the importance of considering item relationships in multimodal data and optimizing key parameters for effective recommendation performance in the SIoT context.

**In Iftikhar et al. 2023**, they explored the potential of Reinforcement Learning in RS, highlighting its adaptability to dynamic environments and its effectiveness in addressing the exploration-exploitation dilemma. They transformed the traditional CF challenge into a sequential decision-making problem using Markov Decision Proces. Employing BiMax and Bibit algorithms for bi-cluster generation from binarized data, they then sorted the bi-clusters based

on quality using the SMSR fitness function. During these phases, they faced challenges in bi-cluster placement within a square grid, especially when exceeding or falling short of grid size. To address this, they merged bi-clusters to fit the grid by combining lower-quality ones with higher-quality counterparts, based on user and item overlap analysis. They then formulated the Markov Decision Process with states, actions, and rewards, and conducted experiments using MovieLens ML-100k and FilmTrust datasets. By reducing dimensions with bi-clustering, they managed large input spaces, leading to evaluations across various metrics, including latency, rewards per episode, exploration-exploitation balance, and the impact of random policies on performance. The results indicated good latency and usual rewards, giving us insights into how well the agent is learning and the effectiveness of its strategies.

**In Himeur et al. 2021,** the emphasis was shifted towards security rather than accuracy and optimization in RS, leading to the design of a blockchain-based RS due to its proven success in ensuring privacy and security. The challenges addressed by blockchain in RS include privacy, trustworthiness, and secure communication, which align with its main features: privacy preservation, secure multiparty computation, and decentralized and collaborative RS. The proposed model architecture for blockchain RS comprises three layers: the Protocol layer manages P2P protocol, consensus algorithm, and data storage; the Extension layer implements RS business logic using smart contracts, and the Application layer. Blockchain-based RS can be categorized into Secure RS, Privacy-preserving RS, and Trust-based RS, applicable across various domains such as Energy, Healthcare, and E-Commerce. However, encountered problems include the difficulty in comparing blockchain-based RS frameworks accurately, limitations faced by newer RS approaches like knowledge-based and deep learning methods due to centralized data processing, sustainability challenges of blockchain protocols, regulatory concerns, interoperability issues, privacy limitations, and addressing data freshness and scalability for blockchain-based RS.

**In Rajput et al. 2023,** the authors introduce TIGER, a novel RS that predicts user preferences using semantic identifiers for items. By generating Semantic IDs and training a model to anticipate these identifiers from user behavior, TIGER outperforms existing RS and excels in recommending novel items to users. The method begins by creating Semantic IDs using pre-trained content encoders, which transform item features into semantic embeddings. These embeddings are quantized to form Semantic IDs using the Residual-Quantized Variational AutoEncoder (RQ-VAE) technique, ensuring diverse representations. Additionally, a generative retrieval approach is proposed, where the model predicts the Semantic ID of the next item in a user’s sequence, leading to personalized recommendations. Experiments on real-world datasets demonstrate TIGER’s superior performance, showcasing significant improvements in metrics like NDCG and Recall. Moreover, the authors address the issue of invalid IDs by suggesting

methods such as increasing the beam size and filtering out invalid IDs. They also propose an extension involving prefix matching to handle invalid tokens, potentially enhancing performance further. Furthermore, TIGER introduces two new capabilities to recommendation systems: cold-start recommendations and recommendation diversity. Cold-start recommendations leverage item semantics to recommend newly added items, while recommendation diversity is achieved through temperature-based sampling during decoding, enabling control over prediction diversity across different levels of hierarchy enabled by TIGER’s unique Semantic IDs.

**In Wang et al. 2018,** they address the challenges of implementing recommender systems in streaming data scenarios, where data is continuously and rapidly produced. Traditional recommender systems, designed for offline settings, struggle with the large volume and high velocity of streaming data. The study investigates the problem of streaming recommendations facing higher input rates than what system resources can immediately process. To tackle these challenges, the authors propose the SPMF (Stream-centered Probabilistic Matrix Factorization) model, based on the Bayesian Personalized Ranking (BPR) optimization framework, for efficient ranking-based recommendations in streaming environments. The SPMF model leverages stochastic gradient descent for online updates, reservoir sampling to maintain historical data, and a novel Gaussian classification model to sample data efficiently, addressing overload, long-term interest retention, interest drift, and the introduction of new users or items. Experiments on three real-world datasets demonstrate the effectiveness of the SPMF model in online recommendation scenarios.

**In Meng, Lin, and Wu 2024,** the authors introduce a novel preference learning method utilizing Graph Neural Networks (GNNs) to enhance object ranking accuracy. Traditional parametric methods in preference learning often struggle with balancing expressive power and training efficiency. To address this, the proposed method involves three stages: constructing a preference relation graph with objects as nodes and preferences as directed edges; predicting preference relations through edge classification using a combination of multi-layer perceptron (MLP) and GNNs; and ranking objects by scoring them via a comparator neural network. Extensive experiments on benchmark datasets demonstrate that this GNN-based approach significantly outperforms traditional methods, providing a robust solution for capturing relational data structures and improving the overall accuracy of preference predictions.

**In Burges, Ragno, and Le 2006,** the authors address the challenge of optimizing quality measures in information retrieval, which are difficult to directly optimize because they depend on the sorted order of documents returned for a given query. They introduce a class of algorithms called LambdaRank, which works with implicit cost functions to avoid these difficulties.

The authors describe LambdaRank using neural network models but note that the concept applies to any differentiable function class. They provide necessary and sufficient conditions for the resulting implicit cost function to be convex and demonstrate its simple mechanical interpretation. Through experiments on several datasets, they show significantly improved accuracy compared to a state-of-the-art ranking algorithm and demonstrate that LambdaRank can speed up the training phase of this algorithm. While the paper focuses on ranking tasks, the authors suggest that LambdaRank can be extended to any non-smooth and multivariate cost functions. They propose a method that bypasses the challenges introduced by the sorted order of documents by defining a virtual gradient on each item after the sort, which provides significant benefits for both training speed and accuracy in applications of commercial interest, particularly in the information retrieval domain.

## 3.2 Multi-modal transportation recommendations

With the rising popularity of Multi-modal transportation recommendations (MTR), numerous studies have been conducted, each with its unique approach aiming to achieve improved results. Researchers are actively contributing to this field, incorporating their own perspectives into their work. Below are some of the most notable recent studies conducted in this area.

### 3.2.1 Related work

**The study Campigotto et al. 2016** presents the FAVourite rOUte Recommendation approach, which offers personalized and situation-aware route proposals tailored to users' preferences. FAVOUR operates through three main stages: initialization, preference refinement, and continuous profile updating. Bayesian learning techniques are employed to incorporate information from users, ensuring adaptability and accuracy. The paper proposes an overall framework for devising such a route recommendation system, including initialization procedures, and investigates the achievable accuracy concerning the number of test questions asked. Additionally, a transfer learning strategy is introduced to improve predictions based on a small number of test questions. The study demonstrates the effectiveness of FAVOUR through experimental results, showcasing its performance compared to alternative approaches and state-of-the-art route recommendation systems. Furthermore, the paper discusses challenges and future research directions, highlighting the potential for enhancing user interaction, preference modeling, and real-time traffic integration.

**The study Hao and Yue 2016** presents an optimization model based on dynamic programming to address the optimal organization problem, considering real-world constraints. The model aims to determine the optimal combination strategy of transport modes. The study highlights the complexity of the problem, including its multi-objective nature, nonlinear transportation costs, and various factors affecting container arrival delays. Existing container multimodal transport optimization models often overlook several key aspects, such as the ability to choose between multiple transportation modes at trade network nodes, the necessity of intermodal convergence at nodes, and the impact of time on transport costs. The empirical study showcases the feasibility and efficiency of the proposed model, exemplified by a case study involving the shipment of ten standard containers from Shenyang to Chengdu via multiple nodes. By employing dynamic programming, the study effectively addresses the complexity of the problem and provides insights into optimizing multimodal transport routes.

**In H. Liu, Li, et al. 2019,** the authors introduced Trans2Vec, a novel framework for MTR, derived from a meticulously constructed transportation graph. Major contributions include formal problem definition, proposing Trans2Vec as a unified solution for transport mode rec-

ommendations. Utilizing historical travel behaviors and user/OD relevance, Trans2Vec offers real-time suggestions. Extensive experimentation on real-world datasets validates the framework’s effectiveness. Notably, Trans2Vec has been successfully integrated into a popular navigation app, benefiting millions of users daily. The study outlines a methodology involving the extraction of a transportation graph from large-scale map query data, optimization solutions, and the integration of user and OD relevance. Evaluation metrics such as NDCG2, precision, recall, and F1 score were employed to assess Trans2Vec’s performance using datasets from Beijing and Shanghai, collected between April 1, 2018, and August 20, 2018

**For the study Abedalla et al. 2019,** the authors introduce MTRecS-DLT, a model for recommending transport modes to users, combining Convolutional Neural Network and Gradient-Boosted Decision Trees through weighted averaging. Leveraging a publicly available dataset from the Context-Aware Multi-Modal Transportation Recommendation challenge, context and user attribute data are preprocessed before concatenation. Results show that ensembled DNN, CNN, CNN-LSTM, and XG Boost models perform best, achieving a F1-score of up to 0.67528288, followed closely by other ensembled models. The DNN model records the lowest F1-score of 0.66892017

**In H. Liu, Tong, et al. 2020,** the authors introduce Hydra, a novel multi-task deep learning-based recommendation system tailored for multi-modal transportation planning. Hydra adapts to various situational contexts, such as nearby point-of-interest distribution and weather conditions, to offer intelligent recommendations. Leveraging existing routing engines and urban data, they propose a two-level framework that integrates uni-modal and multi-modal routes, along with diverse urban data, for robust transportation recommendation. By incorporating user implicit feedback, they learn latent representations of users, origin-destination pairs, and transportation modes, capturing collaborative mode preferences. They introduce two recommendation models: a lightweight gradient boosting decision tree model and a multi-task wide and deep learning model. Hydra has been deployed on Baidu Maps, answering over a hundred million route queries from millions of users since August 2018. Real-world urban-scale experiments demonstrate Hydra’s effectiveness and efficiency.

**The paper Y. Liu et al. 2021,** explore the problem of large-scale MTR and propose a novel travel mode recommendation system for a multi-modal transportation system. The proposed model focuses on feature engineering tailored to the application scenario of MTR, considering users, travel modes, locations, and query time. To improve representation learning, the authors construct a bipartite graph for Origin-Destination pairs and User-OD pairs from query records, transforming nodes into feature vectors using graph embedding techniques. Additionally, a post-processing technique is proposed to handle inconsistencies between the objective function

and the evaluation metric. Experimental results from a city-wide MTR indicate that the proposed model outperforms existing methods employed by navigation service providers.

**In Xu et al. 2023**, a novel MTR algorithm named (Transportation recommendation algorithm with Heterogeneous graph Attention Networks) is introduced, leveraging carefully constructed heterogeneous graphs. THAN comprises four major components: Bigraph, Heterogeneous graph, Hierarchical attention, and Fusion neural layer. The authors propose a Multi-Bigraph Embedding method (MBigraphE) to capture latent features representing relationships between origins, destinations, OD pairs, and users, and design a hierarchical attention mechanism with residual blocks to effectively utilize the semantics of transportation graphs. Extensive experiments on a large-scale real multi-modal transportation dataset demonstrate THAN’s superiority over five state-of-the-art algorithms across four metrics, with optimal performance achieved using a dimension of 64 in the heterogeneous structure.

**In H. Liu, Han, et al. 2023**, the authors delve into the realm of MTR, exploring unified multi-task route representation learning. They leverage both spatiotemporal dependencies from transportation networks and semantic coherence from historical routes. Introducing a hierarchical multi-task route representation learning framework, they propose various modules. Firstly, they transform the multi-modal transportation network into time-dependent multi-view transportation graphs, utilizing a graph-based contextual encoder to fill in missing traffic conditions. Next, a spatiotemporal graph neural network captures spatial and temporal autocorrelation, while a coherent-aware attentive route representation learning module explicitly models route coherence. Furthermore, they incorporate a hierarchical multi-task learning module to differentiate route representations for different transport modes. The authors also introduce spatiotemporal pre-training strategies to enhance model generalization. Experimental results on real-world datasets demonstrate the effectiveness of the proposed system against existing baselines.

**The study Yang et al. 2024**, focuses on recommending door-to-door space-time paths within an intercity multimodal transport network, incorporating modes like railway, metro, bus, rapid-bus, and walking. Through a reconstructed space-time path planning model, various constraints including acyclic, flow balance, and transfer constraints are considered to ensure path viability, differing significantly from traditional graph theory and road networks. The study introduces the Improved Ripple-Spreading Algorithm to attain the K shortest paths, accompanied by a method to reduce the search space for expedited computation. Transport data encompassing urban public transport, railway, and transfer data is analyzed, providing insights into path planning between two cities. Using real-life transit data, the study aims to solve the path planning problem from Taiyuan to Beijing within an intercity multimodal

transport network. Through detailed analysis and experimentation, the study demonstrates the feasibility and effectiveness of the proposed approach.

### 3.2.2 Comparative Table

The table below provides a comprehensive summary of proposed Multimodal Transport Recommendation Systems, highlighting key studies and their methodologies. Each entry includes details such as authors, publication year, title, dataset used, recommendation methods employed, trajectory generation techniques, and outcomes achieved. This table serves as a structured overview, showcasing how different approaches contribute to enhancing decision-making and optimizing trajectories within multimodal transport networks.

Table 1: Summary of Multimodal Transport Recommendation Systems

Approach proposed in	Focus	Used dataset	Used methods	Evaluation Results
Campigotto et al. 2016	Personalized and situation aware.	Travel choices made by 40 participants from diverse demographic groups.	Bayesian learning.	Mean predictive accuracy: 0.723
			Transfer learning.	
			Stated preference survey.	
H. Liu, Li, et al. 2019	Personalized recommendations for multimodal transportation routes, accommodating various modes.	Travel events recorded from map queries and user feedbacks on the Baidu Map in Beijing and Shanghai.	Anchor embedding technique.	NDCG: 0.893
			Joint representation learning framework.	PREC: 0.700
				REC: 0.770
				F1: 0.711
Continued on next page				

Approach proposed in	Focus	Used dataset	Used methods	Evaluation Results
Abedalla et al. 2019	Recommend the most appropriate transport mode to each user.	The public dataset from the Context Aware Multi-Modal Transportation Recommendation challenge, released on April 10th, 2019, which includes historical user behavior data from Baidu Map.	Convolutional Neural Network. Gradient Boosted Decision Trees.	Weighted F1-score: 0.68898702
H. Liu, Tong, et al. 2020	Multimodal transportation plan that adapts to various situational contexts.	Baidu Maps data, covering user behavior data from September to November 2018.	Light-weight gradient boosting decision tree . Multi-task wide and deep learning .	F1: 0.414 PRE: 0.286 REC: 0.748 NDCG: 0.805
Y. Liu et al. 2021	Various combinations, while extracting features related to user preference, mode accessibility, and location popularity.	Real travel mode choice data from Baidu Maps, covering around 2 million historical recommendations and user behaviors.	Bipartite graph. Graph embedding technique.	Weighted F1 between 0.6041 and 0.7936
Continued on next page				

Approach proposed in	Focus	Used dataset	Used methods	Evaluation Results
Xu et al. 2023	Recommend the most suitable transport mode for users.	Navigation data from Baidu Maps, including user attributes, origin, destination, and transport mode data.	Heterogeneous graph Attention.	F1: 0.7566
			Graph neural networks.	PRE: 0.797
			Graph embedding.	REC: 0.7848
				NDCG: 0.9523
H. Liu, Han, et al. 2023	Unified route representation for multimodal transportation recommendation, leveraging spatiotemporal dependencies and semantic coherence of historical route.	Real-world transportation data from Beijing and Shanghai, provided by a leading navigation application.	Graph-based contextual encoder.	Hit between 0.8716 and 0.9235
			Spatiotemporal pre-training strategies.	NDCG between 0.8735 and 0.8983
Continued on next page				

Approach proposed in	Focus	Used dataset	Used methods	Evaluation Results			
Yang et al. 2024	Outputs a K shortest path planning framework for intercity door-to-door travel.	Urban public transport data, including bus and metro route information, railway data detailing train schedules and station locations, and transfer data indicating transfer times between stations.	Algorithm inspired by the ripple-spreading phenomenon.	<table border="1"> <tr> <td data-bbox="1195 390 1513 478">Average Path-finding time/s: 80 s</td> </tr> <tr> <td data-bbox="1195 478 1513 562">Minimum Path-finding time/s: 0.04 s</td> </tr> <tr> <td data-bbox="1195 562 1513 646">Maximum Path-finding time/s: 530 s</td> </tr> </table>	Average Path-finding time/s: 80 s	Minimum Path-finding time/s: 0.04 s	Maximum Path-finding time/s: 530 s
Average Path-finding time/s: 80 s							
Minimum Path-finding time/s: 0.04 s							
Maximum Path-finding time/s: 530 s							

### 3.2.3 Synthesis

After reviewing the various studies presented in the current chapter, it is evident that these works extensively utilize advanced machine learning and deep learning techniques to enhance recommendation systems. For instance, convolutional neural networks and gradient-boosted decision trees are commonly employed to handle complex data and improve model performance. Additionally, many studies incorporate graph-based methodologies to model the relationships between users, origin-destination pairs, and transport modes. This approach is exemplified in the use of bipartite graphs Y. Liu et al. 2021 and heterogeneous graphs Xu et al. 2023.

However, each study adopts a different approach in its recommendation and trajectory generation methods. For recommendation generation, the following approaches were identified:

- Bayesian Learning and Transfer Learning: Utilized in Campigotto et al. 2016 to continuously update user profiles and apply pre-existing knowledge for route recommendations.
- Optimization Modeling: Employed in Hao and Yue 2016 who use dynamic programming for optimizing container multimodal transport systems.
- Joint Representation Learning: Implemented in H. Liu, Li, et al. 2019 who employ a multi-modal transportation graph to learn representations for recommendation.
- Multi-Task Deep Learning Systems: Utilized in H. Liu, Tong, et al. 2020 who use a combination of light-weight GBDT and multi-task wide and deep learning (MTWDL) for context-aware recommendations.

For trajectory generation, the following methods were identified:

- Graph Embedding Techniques: Constructed bipartite graphs and transformed nodes into feature vectors as done in Y. Liu et al. 2021.
- Heterogeneous Graph Attention Networks: Utilized a hierarchical attention mechanism to generate node embeddings as done in Xu et al. 2023.
- Time-Dependent Multi-View Transportation Graphs: Transformed transportation networks into multi-view graphs and employed a graph-based contextual encoder as done in H. Liu, Han, et al. 2023.
- Ripple-Spreading Algorithm: Utilized an improved ripple-spreading algorithm to find the K shortest paths in intercity multimodal transport networks as done in Yang et al. 2024.

The datasets used also vary significantly from one study to another, with some studies focusing on city-specific data while others utilize broader datasets covering multiple cities and transport modes. Additionally, many datasets are confidential.

The outputs of these systems also differ, aligning with the objectives of the respective applications:

- **Personalization and Context Awareness:** Achieved through dynamic user profiles and consideration of situational factors like weather H. Liu, Tong, et al. 2020; Campigotto et al. 2016.
- **Optimal Transport Strategies:** Effective strategies for container transport systems and other multimodal transport scenarios Hao and Yue 2016.
- **Unified Route Representation:** Leveraging spatiotemporal dependencies for robust recommendations H. Liu, Han, et al. 2023.
- **Efficiency in Computation:** Improved algorithms for faster and optimal path planning Yang et al. 2024.

In conclusion, while all the studies aim to improve multimodal transport recommendation systems, they differ significantly in their methodologies, data utilization, and specific outcomes. The common thread across these studies is the use of advanced machine learning techniques and the integration of diverse data sources to provide accurate, personalized, and context-aware recommendations. These similarities and differences highlight the evolving landscape of multimodal transport recommendation systems and the continuous efforts to enhance their performance and user satisfaction.

## 4 Conclusion

In this report, we have presented the state of the art in recommendation systems for multimodal transportation in smart cities. We began by discussing the main themes surrounding this topic in the first chapter. Initially, we provided a comprehensive overview of recommendation systems in general, exploring their methodologies, applications, and evaluation metrics. Following this, we delved into the concept of smart cities, highlighting the key technologies and challenges they face. Finally, we examined multimodal transportation systems, emphasizing their importance in urban mobility and smart city planning.

In the second chapter, we focused on recent developments in recommendation systems. We presented a detailed review of several recent works, showcasing innovative approaches and methodologies that have been proposed in this field. Additionally, we explored various approaches specific to multimodal transportation recommendation systems. In this context, we observed a wide range of strategies, each contributing uniquely to the advancement of this domain. These approaches demonstrate the ongoing efforts to enrich the field and address the complex challenges associated with integrating different modes of transportation to provide seamless and efficient mobility solutions.

In conclusion, this report underscores the significant progress made in the intersection of recommendation systems and multimodal transportation within smart cities. Our findings indicate that continuous innovation and interdisciplinary research are essential for further advancing this field and addressing the evolving needs of urban environments.

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