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Review

Emerging Perspectives on the Application of Recommender Systems in Smart Cities

Gricela Andrade-Ruiz [1], Ramón-Alberto Carrasco [2,*], Carlos Porcel [3], Jesús Serrano-Guerrero [4], Francisco Mata [5] and Mario Arias-Oliva [6]

[1] Faculty of Economics and Business, Complutense University of Madrid, 28223 Madrid, Spain; gricelan@ucm.es
[2] Department of Marketing, Faculty of Statistics, Complutense University of Madrid, 28040 Madrid, Spain
[3] Department of Computer Science and Artificial Intelligence, University of Granada, 18071 Granada, Spain; cporcel@decsai.ugr.es
[4] Department of Information Technologies and Systems, University of Castilla-La Mancha, 13071 Ciudad Real, Spain; jesus.serrano@uclm.es
[5] Information Technology Department, University of Jaén, 23071 Jaén, Spain; fmata@ujaen.es
[6] Department of Marketing, Faculty of Economics and Business, Complutense University of Madrid, 28223 Madrid, Spain; mario.arias@ucm.es
* Correspondence: ramoncar@ucm.es

Abstract: Smart cities represent the convergence of information and communication technologies (ICT) with urban management to improve the quality of life of city dwellers. In this context, recommender systems, tools that offer personalised suggestions to city dwellers, have emerged as key contributors to this convergence. Their successful application in various areas of city life and their ability to process massive amounts of data generated in urban environments has expedited their status as a crucial technology in the evolution of city planning. Our methodology included reviewing the Web of Science database, resulting in 130 articles that, filtered for relevancy, were reduced to 86. The first stage consisted of carrying out a bibliometric analysis with the objective of analysing structural aspects with the SciMAT tool. Secondly, a systematic literature review was undertaken using the PRISMA 2020 statement. The results illustrated the different processes by which recommendations are filtered in areas such as tourism, health, mobility, and transport. This research is seen as a significant breakthrough that can drive the evolution and efficiency of smart cities, establishing a solid framework for future research in this dynamic field.

Keywords: recommendation systems; smart cities; techniques of filtering; bibliometric analysis

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1. Introduction

Today, cities are undergoing an unprecedented transformation thanks to the implementation of advanced technologies that give them the "smart cities" title [1,2]. This radical change not only redefines urban infrastructure but also significantly impacts citizens' lives, offering new opportunities and innovative services [1].

In smart cities, where the interconnection of devices generates massive data, recommender systems become essential tools to help consumers navigate the abundance of available options and quickly find what best suits their individual needs.

In this scenario, the relevance of recommender systems is further highlighted [2,3]. These systems use advanced algorithms to analyse user behaviour patterns and preferences, providing personalised recommendations for products and services.

In the dynamic fabric of contemporary societies, the intersection between technology and urbanisation has precipitated the rise of two emerging phenomena of great relevance: recommender systems and smart cities. These paradigms, driven by technological advancement and data explosion, have transformed how people interact with information and how cities manage their complex infrastructures.

Initially conceived in the realm of product recommendation on commercial platforms, recommender systems have evolved to become ubiquitous agents in our daily lives. The explosion of digital data has enabled the creation of sophisticated algorithms that anticipate and suggest preferences, from entertainment choices to purchasing decisions. This phenomenon impacts not only the consumer sphere but also how we conceive and navigate our cities.

In parallel, the concept of smart cities has gained momentum in response to the challenges of rapid urbanisation. The emergence of smart cities has become a global phenomenon, underpinned by exponential growth in urbanisation and the pressing need to manage resources more sustainably. In addition, the smart city landscape has been significantly shaped by the COVID-19 pandemic, which has expedited the transformation of urban planning and city management. According to the International Telecommunication Union (ITU) report on smart cities, the number of cities that have implemented such initiatives has seen a 28% increase in recent years, reaching a total of 96 cities by 2023 [1].

The convergence of big data, sensors, and information technologies has enabled the creation of urban environments that proactively respond to citizens' needs. A study by the ITU indicates that 82% of cities surveyed implement some degree of intelligent technologies to improve quality of life [1].

This review forms a solid basis for guiding future research, providing a comprehensive understanding of the current state of knowledge, highlighting areas of opportunity, and encouraging a more informed and reflective approach to smart cities and recommender systems research. This paper reviews the dynamic interplay between recommender systems and smart cities, identifying the recommender system techniques that influence the configuration of smart cities, as well as their areas of application, and how this synergy redefines the urban experience. The review of current studies and analysis of relevant scientific data will seek to understand the mutual influence of these two phenomena in the transformation of our contemporary urban experiences.

The proposed study is positioned as a valuable contribution to the field of smart cities as it is the first study to offer a comprehensive review of the state of the art in the application of recommender systems. This study comprises not only a bibliometric analysis, but also a systematic review of the existing literature to date. It explores case studies, identifies challenges, and highlights opportunities for improvement, underlining the versatility and potential of these systems in different urban contexts.

The structure of the article is as follows: The introduction is followed by the conceptualisation of the terms "smart city" and "recommender system". The methodology section is subdivided into two sections: the first section presents the methodology used to perform the bibliometric analysis, and the second sub-section presents the methodology of the systematic review. The results and discussion section analyses the various results obtained and is divided into four subsections that address each research objective, respectively. Finally, the last section presents the conclusions of the study.

2. Fundamentals of Smart Cities and Recommender Systems

For the comprehensive development of the article, it is imperative to establish clear definitions of both smart cities and recommender systems, outlining their fundamental elements. A precise understanding of these concepts is essential to contextualise the analysis and effectively explore the application of recommender systems in the dynamic environment of smart cities.

2.1. Background of Smart Cities

Smart cities are an evolution of traditional urbanisations. The difference is that they incorporate the use of technology and digitalisation to improve the quality of life of their inhabitants due to their rapid growth. Factors such as traffic congestion, scarcity of resources, pollution, or lack of efficiency in the management of services have led to their development [2]. The origin of smart cities dates back to the end of the 20th century when new ways of managing cities through technology began to be explored [3]. This movement was driven by advances in the Internet of Things (IoT), which enabled the interconnection of physical objects and their control through the internet. One of the first cases of technology application in a city was in 2010, where in the city of Santander, Spain, an extensive network of sensors was installed to monitor different aspects of the city, such as air quality, traffic, and energy consumption [4].

The implementation of technology has been replicated in many cities around the world to provide solutions that improve inhabitants' quality of life [4]. Solutions include intelligent transport systems that enable better traffic management, efficient public transport systems, and the promotion of sustainable modes of transport. This reduces road congestion, improves mobility, and benefits the environment by reducing carbon emissions [5]. Another solution is smart energy management, which reduces consumption and encourages the use of renewable energy [6]. With the construction of smart electricity infrastructures, the integration of renewable energies, decentralised management, and energy consumption has been achieved [7]. These constructions allow the monitoring and control of energy consumption through the use of sensors and smart metering systems to collect real-time data [8], for example, on the energy consumption of buildings, public lighting, and transport, among others, allowing more accurate and efficient control of consumption [9]. Technology enables greater interaction between citizens and governments, cultivating collaboration and engagement in urban policy planning. In addition, the aim is to develop technological solutions that improve the quality of life of citizens, such as mobile applications for transport management, health, or safety [10].

The implementation of smart cities is not without its challenges. One of the main challenges is social inclusion and equity in access to technology [11]. It is important to ensure that all citizens can benefit from the improvements offered by technology, thus avoiding the digital divide. In addition, ethical and privacy aspects must be considered when using smart systems' data [12]. For Logesh et al. (2018) [13], the deployment of smart technologies allows the provision of higher quality and more efficient public services. For example, smart waste collection systems that optimise collection routes and reduce pollution have been implemented. Smart lighting systems that adapt light intensity according to needs have also been established, improving safety [14].

Definitions of a Smart City

The rapid advancement of technology has triggered significant transformations in the organisation of our societies. One of the most prominent manifestations of this change can be found in the concept of "smart cities", which is discussed below, according to the contributions of different authors [15].

According to Li et al. (2023) [16], a smart city is a city that uses technology and innovation to improve the quality of life of its inhabitants, optimising the efficiency of public services such as transport management, energy supply, waste and water management, public safety, provision of public services, reduction of environmental impacts, and promotion of civil participation. According to Arnaoutaki (2021) [17], for a city to be smart, it must use sensors and connected devices to collect data in real time, then analyse and use it to make smart decisions that improve urban management. The main goal of a smart city is to use technology to provide more efficient, sustainable, and accessible services to its citizens [17]. In addition, a smart city encourages civil participation and promotes collaboration between the public, private, and civil society sectors to generate innovative solutions and improvements in the quality of life of its inhabitants.

2.2. Recommender Systems

In the age of digitised information, the phenomenon of data overload has led to the emergence and development of recommender systems, a critical piece at the intersection of artificial intelligence, data analytics, and the personalisation of user experience [18]. These systems, designed to provide accurate suggestions in e-commerce environments, have expanded into various areas of everyday life [19]. Cities are adopting smart technologies to improve the quality of life of their inhabitants and optimise the use of resources. One of these key technologies is recommender systems [20]. These systems provide citizens with personalised and relevant information about various aspects of the city, working through data collection [21]. For this, sensors distributed throughout the city are used to capture real-time information [14]. These sensors can measure variables such as temperature, air quality, noise, and traffic, among others [22]. In addition, data is also collected from citizens themselves through mobile applications or online platforms [6]. Once the data has been collected, it is processed using advanced data analysis algorithms and artificial intelligence [23]. These algorithms are able to analyse large amounts of information in real time and detect patterns and correlations between different data [24]. In this way, the recommender system can provide personalised suggestions based on the preferences and needs of each individual.

The smart city recommender system offers tailored recommendations, spanning cultural events, leisure activities, restaurants, and shops, based on individual preferences [24]. In order to provide accurate and relevant suggestions, the smart city recommender system must also be able to learn and adapt continuously. That is, it must be able to identify the changing preferences and needs of citizens as they evolve over time [25]. For this reason, the system uses machine learning techniques and real-time analytics to improve its accuracy and provide increasingly accurate suggestions. Recommender systems can help citizens make more efficient energy consumption decisions [26]. This is a highly relevant issue, given the rapid growth of the world's population and the increase in economic activities [2]. Energy consumption is closely related to the economic development of a country [6]. As a society develops, its energy demand increases for activities such as the production of goods and services, transport, and the heating of homes. This increase in energy demand can greatly affect the environment, as most energy sources are non-renewable, such as fossil fuels (oil, natural gas, and coal) [27].

This phenomenon has brought with it an increase in extreme natural phenomena, such as hurricanes, droughts, and floods, which affect millions of people globally. Recommender systems can inform citizens on how to use the energy in their homes and suggest more efficient and environmentally friendly public transport routes. They show how much energy a household consumes, and, by raising such awareness, this will likely decrease [28]. Recommender systems can improve urban mobility by helping citizens find optimal public transport routes, avoid congested areas, and hire shared transport services [28]. This can contribute to a reduction in traffic, a reduction in greenhouse gas emissions, and an improvement in mobility in the city. However, as mentioned above, there exists a handicap for older adults who have difficulty learning and are somewhat isolated from technology, so an emphasis would need to be placed on helping them adapt.

On the other hand, recommender systems often learn from people's preferences and behaviours. This means that users may receive recommendations based solely on their previous preferences, limiting their exposure to new ideas, opportunities, and experiences [29].

In addition to this information bias, consumers may encounter a lack of diversity where recommendation algorithms tend to highlight content that is popular or similar to what the user has previously consumed. Recommender systems also affect privacy and security. When accessed, a lot of users' personal data is collected and used; if misused or leaked, users can be negatively affected. The manipulation of opinions to promote certain products, services, or ideas over others can more easily occur. This can lead to a lack of transparency and fairness in recommendations, as well as undue influence on users' decisions [30].

Finally, technological dependency is created by the constant use of recommender systems: users may become dependent on these technologies to make decisions [12]. Owing to a lack of autonomy and choice, users may rely on recommendations without questioning them or looking for other options.

2.2.1. Techniques of Recommender Systems

In the context of smart cities, recommender systems refer to tools and technologies that use algorithms and data analysis to provide suggestions, advice, or personalised information to citizens with the aim of improving their experience and quality of life in urban environments. These systems make use of the interconnection of devices, sensors, and data available in smart cities to provide useful and relevant recommendations in areas such as mobility, public services, urban planning, and civil participation.

Recommender system techniques allow us to select and rank items that are suggested to the user [31]. This may include the exclusion of certain elements that do not meet certain criteria or the ranking of recommended elements based on their relevance to the user [32]. There are different classifications of recommender systems; a more general one includes these five types:

- Collaborative Filtering: This recommender system uses information about other users' preferences to provide personalised recommendations. It is based on the idea that if two users had similar tastes and preferences in the past, they are likely to have similarities in the future as well. This system analyses user behaviour and looks for patterns to predict which products or items might interest them [33].
- Knowledge-Based Filtering: This starts from a predefined knowledge base about the recommended items [34]. It uses explicit information about the products or items, such as attributes, features, or labels, to make recommendations. However, it does not take into account the preferences or behaviours of other users but relies instead on a detailed description of the available items [35].
- Demographic Filtering: This system uses demographic information about users to make recommendations. It is based on characteristics such as age, gender, geographic location, profession, etc., to identify patterns that may influence user preferences [36].
- Content-Based Filtering: This is based on the analysis of the content of the items to be recommended. It uses characteristics and attributes of the items (such as tags, categories, genre, director, etc.) to look for similarities between the items [29]. For example, if a user previously liked romantic comedy films, the system will use that information to recommend similar movies in the future.
- Hybrid: Hybrid recommender systems combine different approaches to provide more accurate and personalised recommendations. They can combine several systems, such as collaborative and content-based filtering, to take advantage of the benefits of each approach [37].

2.2.2. Recommender System Indicators

Recommender system indicators are metrics or measures used to evaluate and measure the effectiveness and performance of a recommender system [38]. These indicators, are used to quantify the degree of accuracy, relevance, and usefulness of the recommendations provided by the system [39]:

- Data Collection: This indicator assesses whether obtaining and collecting the information needed to generate recommendations is possible. This includes examining available data sources, such as transaction logs or user preferences [3].
- Algorithms and Models: These enable the processing and analysis of data collected. It is important to consider whether algorithms can handle large volumes of data and generate accurate recommendations to users while working internally to evaluate for continuous improvement in smart cities [40].
- Technological Infrastructure: This indicator assesses whether the necessary technological infrastructure is in place to implement and run the recommender system. This may include servers, databases, and computing resources such as connectivity, which measures the quality and availability of communications networks, such as high-speed internet access and mobile network coverage [41].
- Data Platforms: This indicator assesses the presence of technological platforms that enable the storage, processing, and analysis of large volumes of data generated by the

city, as well as the ability to share this data with different relevant stakeholders. The presence and operation of sensors and smart devices enables real-time data collection to manage different aspects of the city, such as traffic, waste management, security, etc. [8].

- Costs: This indicator analyses the costs associated with developing, implementing, and maintaining the recommender system [24]. This may include the cost of software acquisition or development, as well as data storage and processing costs.
- Benefits and Business Value: This indicator assesses the potential benefits and business value that the recommender system can bring to an organisation [42]. This looks at increased sales, improved customer experience, or generating additional revenue through personalised recommendations [43].
- Performance Evaluation: This indicator conducts real-time testing and evaluation to measure the accuracy and effectiveness of the recommender system. This may involve comparing the recommendations generated with actual user preferences and behaviours.

3. Methodology

The initial phase of our literature review involved formulating the research objectives, which served as the basis for defining the scope of the study and guiding the review process [44]. The systematic review was designed to explore the current application status of recommender systems in smart city development.

The research objectives that guided this study were as follows:

O1. To describe how recommender systems and smart cities are structured as a research discipline.

O2. To identify in which areas of application for recommender systems in smart cities are being developed.

O3. To identify what types of recommender systems are being used in smart city studies.

O4. To contrast the types of recommender systems being used according to the application areas in smart cities.

In order to carry out the objectives of this study, two types of analysis will be carried out. A bibliometric analysis following the methodology of Cobo et al. (2012) [45] will allow us to respond to research objective 1. Objectives 2, 3, and 4 will be achieved with a systematic literature review following the PRISMA 2020 statement.

3.1. Bibliometric Analysis

In order to position our work in relation to what has been accomplished in the field, in this section, we will first construct a bibliometric mapping of the combined use of both topics [46]. Scientific mapping, or bibliometric mapping, is an important research topic in the bibliometric field; it aims to show the structural and dynamic aspects of scientific research to enable its interpretation [47]. We followed a methodology inspired by [47] and used the SciMAT version 1.1.04 tool to obtain a bibliometric map with data from the beginning of January 2000 to the end of December 2023.

The first phase involves retrieving the data. Thus, bibliographic records were downloaded from the Web of Science core collection using the query set out in Figure 1.

TS=(("RECOMMEND* SYSTEM*" OR "COLLABORA* FILTER*" OR "CONTENT*-BASED FILTER*" OR "CONTENT* BASED FILTER*" OR "DEMOGRAPHIC* FILTER*" OR "KNOWLEDGE*-BASED FILTER*" OR "KNOWLEDGE* BASED FILTER*") AND ("SMART* CIT*" OR "CIT* 2.0" OR "INTELLIGENT* CIT*" OR "DIGITAL CIT*"))

1:36 PM | Timespan: 2000-01-01 to 2023-12-31 (Publication Date)

Figure 1. Research query.

Here, the TS field is a search based on a specific topic (title, abstract, and keywords). After reviewing the 130 retrieved documents, the next phase is preprocessing. In this phase, we eliminated the terms implicit in the search itself: RECOMMENDER SYSTEM and SMART CITY, as they are obviously predominant in the analysis. We also grouped singulars with their respective plurals and acronyms with their corresponding words. Two study periods were established, taking the year 2019 as a reference. The first period spans from 2000 to 2019, while the second period encompasses the years 2020 to 2023. After this, we carried out the remaining phases of the process: network extraction, normalisation, mapping, analysis, and visualisation. The strategy diagrams allowed us to identify the importance of each topic according to two measures: centrality, which is the degree of interaction of a network with other networks, and density, which is the internal strength of the network or keywords describing the topic in any scientific mapping workflow. For a more detailed understanding, the evolution of the themes is analysed, as well as the keywords that make up the network of these themes.

3.2. Systematic Literature Review

Both the database and the search equation used in this literature review are the same as those described in the bibliometric analysis methodology.

Following the guidelines of the PRISMA 2020 statement, Figure 2 details the literature that was reviewed in the full-text analysis. Initially, 130 articles were identified in the Web of Science. During the initial review, these articles' titles, keywords, and abstracts were evaluated for relevance to the research objectives, and all articles were retained. In the screening process, no duplicate articles were found, but those not available in full-text format online were excluded; as a result, 44 articles were eliminated. Next, a comprehensive full-text review was conducted for the remaining 86 articles, where three articles were eliminated as irrelevant to the research objectives. Ultimately, 83 papers were included in the literature review for this study.

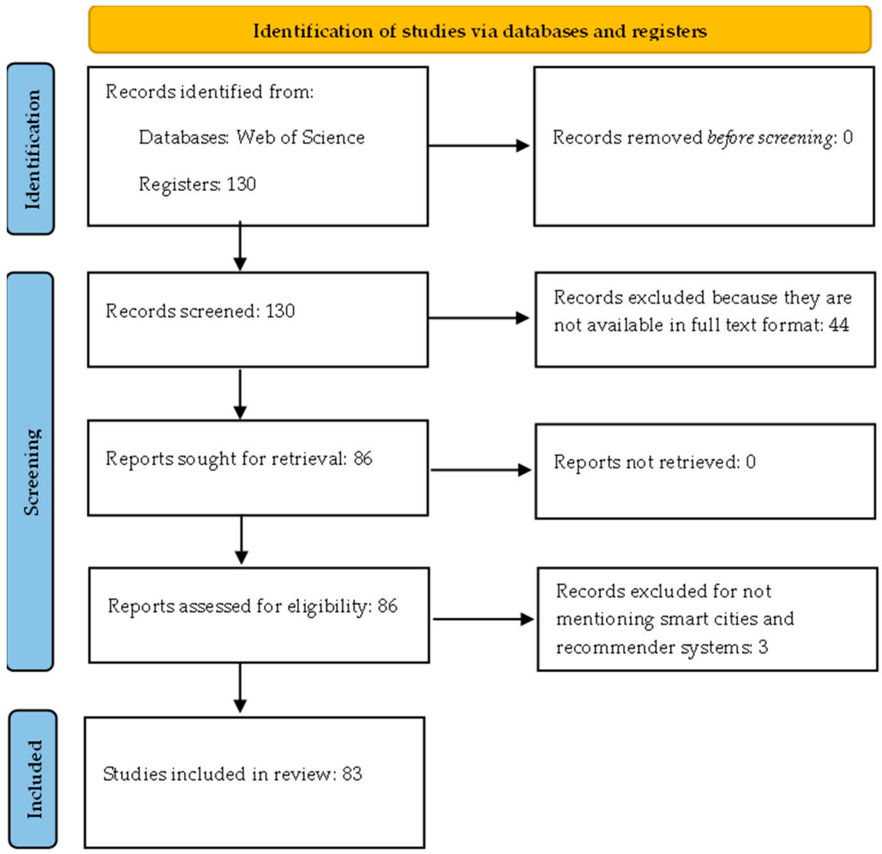


Figure 2. PRISMA 2020 flow diagram.

4. Results and Discussion

In this results and discussion section, we will explore the findings obtained from this study in detail.

The paradigm created by the intersection between recommender systems and smart cities constitutes a topic of interest for the scientific community. Figure 3 shows the increase in the number of papers published on this topic, as well as the number of citations generated.

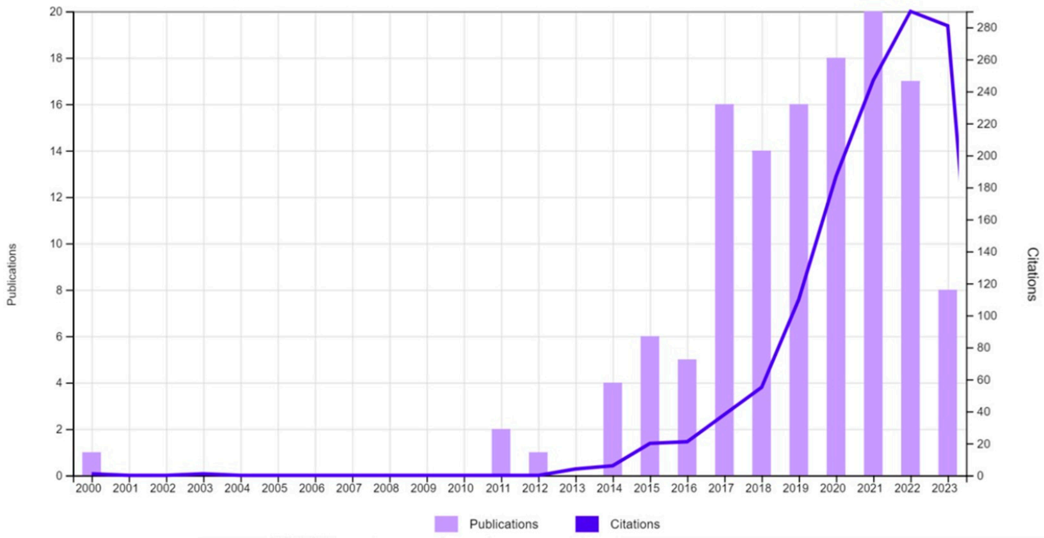


Figure 3. Times cited and publications over time.

A word cloud was generated using VOSviewer version 1.6.16 software to identify the keywords that are the central focus of the definitions of recommender systems and smart cities, as shown in Figure 4. VOSviewer is specifically designed to construct and visualise bibliometric networks, presenting them in a visually comprehensible format [48].

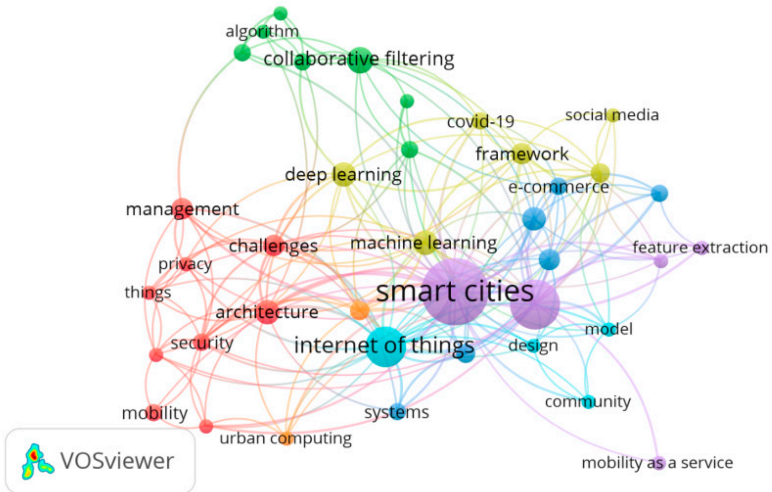


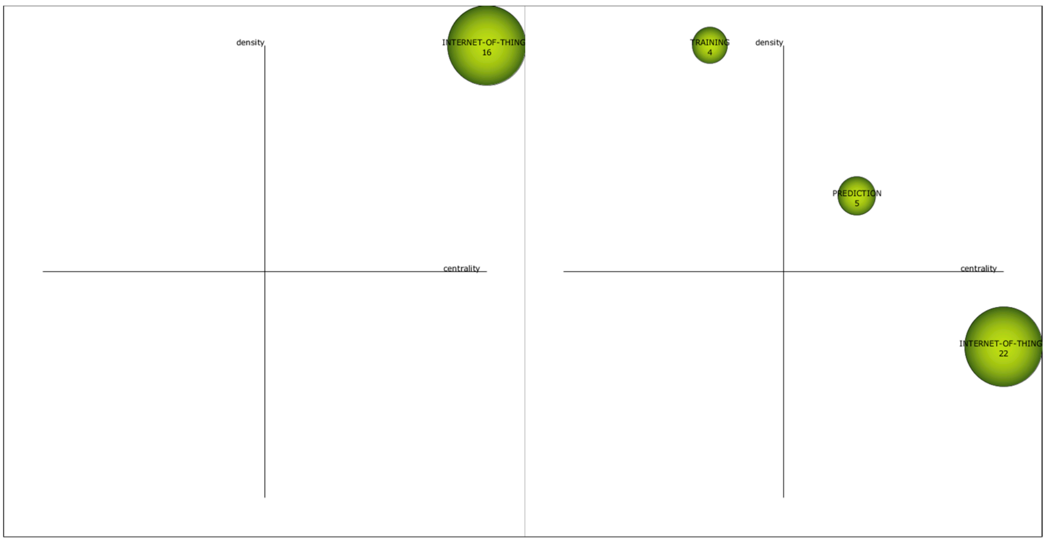
Figure 4. Word cloud of recommender systems and smart cities.

Four main clusters are identified in the word cloud. The first cluster has architecture as its central focus [6,8,41,48]. This refers to the management and distribution of smart cities, in which mobility, privacy, security, management, e-government services, and challenges are analysed. The second cluster has the collaborative filtering technique based on user behaviour as its core. In addition to data, this technique needs elements such as algorithms, crowdsourcing, matrix factorization, and optimisation to operate [19,49–52]. The third cluster gives evidence of the direct relationship between recommender systems, big data, and data mining [53–56] These systems use algorithms and artificial intelligence techniques to analyse past and present user behaviour in order to provide personalised recommendations. These have been exploited to a greater extent in e-commerce. The fourth cluster is mainly based on social media, which provides a predefined structure and functionalities that facilitate the integration of its features into mobile applications and websites [4,27,55–57]. The interest of the scientific community in these topics has increased due to COVID-19 and social distancing, a time during which social media helped maintain social connections and dynamise the economy with deep learning.

4.1. Analysis of the Structure and Evolution of Recommender Systems and Smart Cities as an Area of Research

The strategic diagrams obtained are shown in Figure 5.

The Internet of Things (IoT) refers to the interconnection of physical devices such as appliances, vehicles, and sensors that connect and exchange data with each other through the internet [58]. In addition, through the internet or other communication networks, information can be collected, shared, and used in an automated way [59]. Thus, people have been able to communicate and facilitate task automation, remote monitoring, control of devices, and decision making based on real-time data. The term IoT has been used since 2010, but the idea of connecting objects to the internet has been around for more than 20 years, and it began to gain relevance and be used more frequently in technological and business environments [20,60]. Since then, the IoT has experienced rapid growth and has become one of the main trends in the digital world, and, as can be seen in Figure 5a, it has become a motor theme. Since 2020, this topic has appeared in quadrant 4, located at the bottom right, which includes basic and transversal themes. The main feature of this quadrant is that it covers the most generalised terms. For example, within the technological field are communication systems and the use of sensors and devices to interconnect objects and collect information in real time. The IoT requires knowledge of different technologies such as artificial intelligence, machine learning, and wireless communication [12]. The IoT generates large volumes of data that must be collected, stored, and analysed. For this information to be transformed into a recommender system, it is necessary to use big data, data analysis, and data visualisation techniques [61]. The study of the IoT as a transversal theme allows us to understand its operation and potential, as well as to develop innovative solutions in different fields such as industry, health, and transportation.



(**a**) (**b**)

Figure 5. Strategic diagram of recommender systems and smart cities in the literature. (**a**) Strategic diagram for period 1; (**b**) strategic diagram for period 2.

Within the second period, the motor theme is PREDICTIONS, which allows us to obtain more accurate and timely information, which can be very useful in decision making [61]. TRAINING in this period is identified as a highly developed and isolated topic. This term captures the process of teaching and preparing an IoT system to perform specific tasks [20,62]. This involves using algorithms and machine learning models to analyse the data collected by IoT devices and extract relevant information.

In Figure 6, we expand the topic related to our work and its evolution between the two periods. We also include the keywords that compose the network of those topics.

From the studies of the Internet of Things (IoT), the topics of NE04, DATA MINING, BIG DATA, and GRAPH DATABASE are addressed. These terms are related to each other from a perspective of the creation and analysis of information data [52,63]. These four keywords are explained below:

- NE04: This is a term used to refer to the fourth generation of the electricity grid and describes the integration of information and communication technologies into the power grid to improve its energy efficiency and reliability [52,59,63,64].
- DATA MINING: The process of discovering hidden patterns, trends, and relationships in large amounts of data [65]. It uses techniques and algorithms to analyse large data sets so that valuable information can be discovered to make strategic decisions and improve an organisation's performance [10,40,52,65].
- BIG DATA: This refers to the large amount of data that is generated daily through different sources such as social networks, online transactions, smart devices, and sensors, among others. It also describes the set of tools, techniques, and technologies needed to capture, store, manage, and analyse large amounts of data [53,66,67].
- GRAPH DATABASE: A type of database designed to store and manage information in the form of graphs. A graph consists of nodes (entities) and arcs (relationships) connecting the nodes. The network database represents and analyses complex relationships between entities, allowing more efficient modelling and analysis of interconnected data. [68,69].

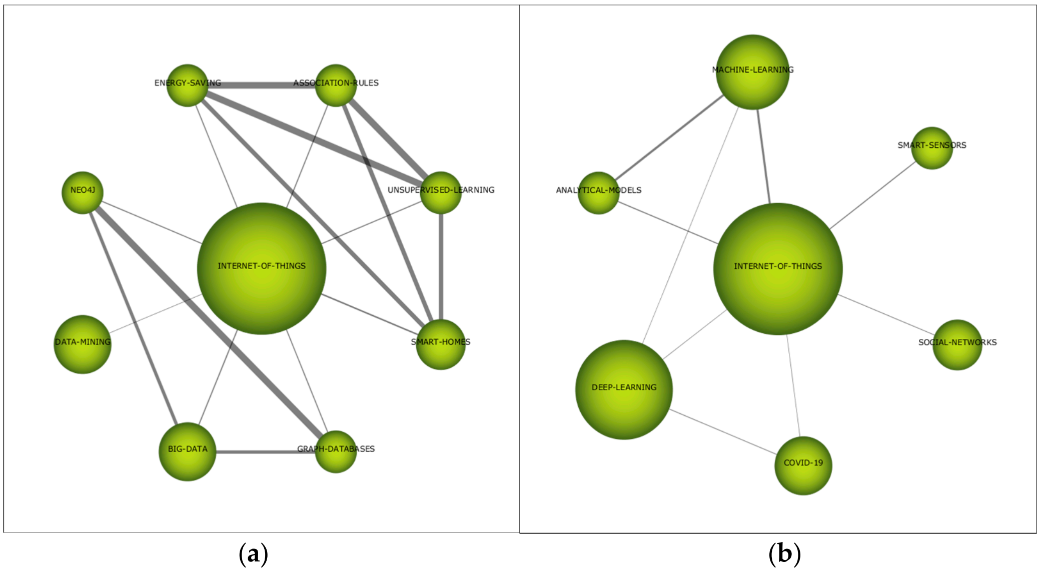


Figure 6. Cluster network of the Internet of Things. (**a**) Period 1 cluster network; (**b**) period 2 cluster network.

On the other hand, we observe another set of topics that are also related such as: ENERGY SAVING, ASSOCIATION RULES, UNSUPERVISING LEARNING, and SMART HOMES. These terms have similar characteristics that allow the creation of this set of information used in the IoT. Next, we will explain how they intervene.

- ENERGY SAVING: This seeks to optimise energy consumption in connected devices [65]. Sensors and intelligent systems allow measuring and controlling energy use in real time, which facilitates the identification of areas for improvement and the implementation of energy saving strategies [7,70–73].
- ASSOCIATION RULES: Association rules refer to relationships and patterns discovered between data collected by connected devices [56]. These rules allow identifying connections and dependencies between different variables and events, which is useful for making informed decisions based on pattern analysis [74].
- UNSUPERVISED LEARNING: This machine learning technique is used in the IoT to discover patterns and structures in data without explicit supervision [74,75]. These devices collect large volumes of data continuously, and unsupervised learning is useful for detecting anomalies, classifying data, and discovering hidden relationships.
- SMART HOMES: In these homes, devices and systems are interconnected and communicate with each other to provide comfort, security, and energy efficiency [59]. Connected devices in a smart home, such as thermostats, lights, appliances, and security systems, can be controlled remotely and learn from user patterns and preferences to optimise energy use [8].

Figure 6b shows the themes that make up the IoT cluster as of 2020. The DEEP LEARNING and MACHINE LEARNING themes stand out, referring to the global network of interconnected physical devices that collect and share data over the internet using the deep and machine learning offered by each [76]. MACHINE LEARNING and DEEP LEARNING can benefit from the IoT in the following ways: data collection [75], real-time data analysis [56], and predictions that enable decisions based on up-to-date information [21,27,77]. Another theme that makes up this cluster is COVID-19, which is considered a catalyst for the development of smart cities [78], mainly because of the need to maintain physical distance and minimise personal contact [75]. Smart cities offer technologies that enable process automation and the use of sensors to monitor social distancing and ensure compliance with public health measures [78,79]. Smart cities provide advanced digital infrastructures that facilitate connectivity, sensor devices, real-time data availability, and implementation of technological solutions to address pandemic challenges [80]. The development of smart cities is also driven by the rise of SOCIAL NETWORKS, from telecommuting to online education [26]. These models enable improved energy efficiency with increased remote working and reduced mobility, driving energy efficiency and sustainability [78].

4.2. Areas of Application for Recommender Systems in Smart Cities

Smart cities not only seek to address traditional urbanisation challenges, but also aspire to take full advantage of technology to improve the quality of life of their inhabitants.

Figure 7 shows the main application areas identified in this study. By the number of studies conducted in each area, mobility and transport stands out with 25 [41,81], urban innovation with 16 [14,16], cultural heritage and tourism with 11 [5,28,32,82], e-commerce with nine, energy management with eight, and, with less than five studies, we find areas such as e-governance [7], health [83], security [53], geolocation [56], economy [14,36,82], education [25,84], and gastronomy [12].

Applications in a smart city work through a digital infrastructure that can connect different systems and devices [27,85].

Mobility and Transport: In the process of implementing these technologies in smart cities, mobile applications have had a great impact, among which those related to mobility and transportation stand out [1,39,74,85,86]. Applications used worldwide, such as Uber, Lyft, or Citymapper, allow users to find public transport routes, book shared rides, or even rent bicycles or electric scooters. These apps help reduce traffic congestion and promote more sustainable mobility in cities [1,10,56,80].

Urban Innovation: Exploring the field of urban innovation, smart cities operate in a variety of ways tailored to their specific objectives and functions. Broadly speaking, these platforms typically make use of technologies such as the Internet of Things (IoT), big data analytics, artificial intelligence, and sensors to collect, process, and analyse real-time data related to multiple aspects of the city [7,39].

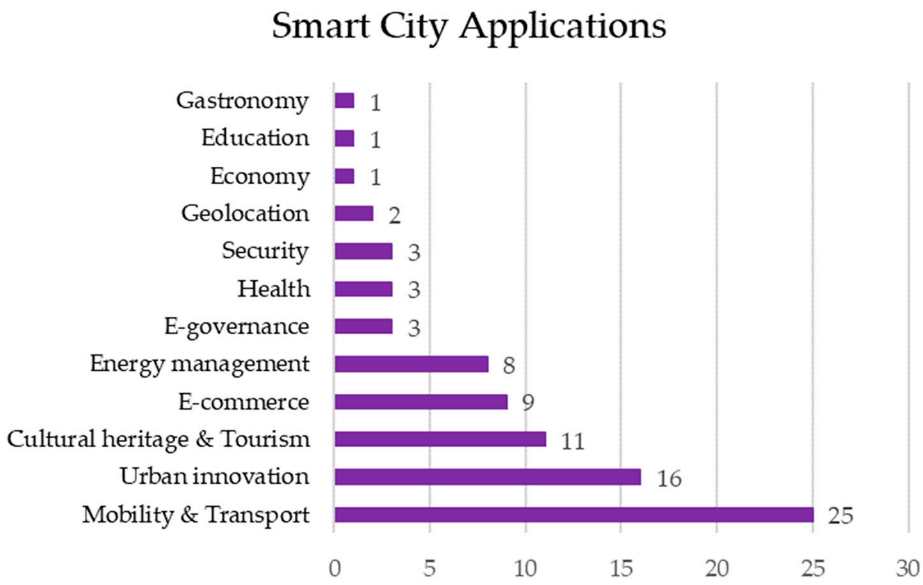


Figure 7. Smart city application domains.

Cultural Heritage and Tourism: In the field of cultural heritage and tourism, these applications operate by providing detailed and instantly updated information on cultural and tourist sites in a specific region. These applications often incorporate features such as interactive maps, tourist guides, opening hours, entrance fees, reviews from other users, and photos and videos, among other relevant data [8].

E-Commerce: In e-commerce, recommender systems help users discover relevant products, improve the shopping experience, and increase customer retention through accurate recommendations tailored to each user's interests and shopping behaviour. Integrating recommender systems can boost efficiency, convenience, and user satisfaction, thus contributing to the creation of smarter city environments and more personalised online shopping experiences [19].

Energy Management: Regarding energy management, applications such as Wattio or WeSmartPark help citizens control and optimise their energy consumption at home or at work [52]. These applications allow real-time data monitoring and offer suggestions to reduce energy consumption, which contributes to sustainability and economic savings [28,56,71].

Security applications are also widely used in smart cities. Citizen, one such application, although its use has been mainly concentrated in the United States, is also available and used in other parts of the world, such as Canada, the United Kingdom, and Australia. This application allows citizens to report incidents or crimes in real time and receive alerts about dangerous events they may be close to [28,87].

Another application of social interest for the community is waste management. Trashout or Recyclebank are well-known apps that help citizens locate the right waste collection points, let them know when containers are full, and promote proper waste separation. However, they work best in smart cities that are aware of the importance of taking care of public and private infrastructure [8,14,70].

In addition to these main areas, there are many other applications used in smart cities, such as those related to e-governance, health, geolocated security, economy, education, and gastronomy [77,88,89]. These applications allow citizens to access information and services more quickly and conveniently while facilitating informed decision making.

4.3. Recommender System Techniques

Recommender system techniques allow the selection and ranking of items to be suggested to the user [90]. This may include excluding certain items that do not meet certain criteria or ranking the recommended items based on their relevance to the user [91].

Figure 8 shows the filtering techniques used in the different studies, ranked by the number of documents each recommender system method used. The most commonly used filtering techniques are collaborative filtering, knowledge-based filtering, and demographic filtering [92]. Collaborative filtering, used in 28 studies, it is the most widely used filtering technique. The works of Ayub et al. (2020) [32] and Sharma, Rani, and Nuagh (2022) [4] particularly stand out. These study the behaviour of citizens to find patterns and predict more energy-efficient products that might interest them. Then there are the works of Quijano-Sánchez et al. (2020) [93] and Mordacchini et al. [29], which, in the political and governmental sphere, seek to establish recommendations according to the description of elements available in the city. Employed in nine articles, knowledge-based filtering is based on user references to plan and create smart cities [14,61,68]. The use of this filtering technique demonstrates how the knowledge of users and professionals makes it possible to formulate recommendations that guarantee efficiency in the creation of applications. The demographic filtering technique used in eight of the articles studied makes it possible to generate recommendations based on databases that collect demographic information such as age, gender, geographic location, profession, etc. [35,41,48]. The creation of user profiles will allow the development of more precise recommendations to work in different areas [53]. Content-based filtering is employed in four studies and serves to systematise through existing content; for example, if a user showed his preferences in the past, recommendation systems using this filtering technique will recommend similar products and services in the future [26,33,94].

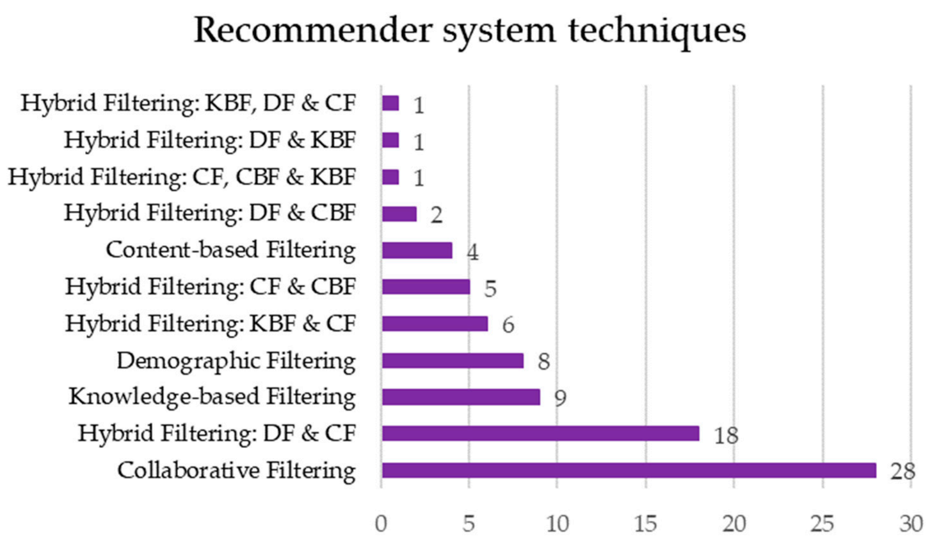


Figure 8. Filtering techniques.

In addition to using these pure filtering techniques, studies show a growing interest in hybrid recommender systems. Hybrid systems allow combining more than one type of filtering technique. The combined use of demographic filtering and collaborative filtering (DF and CF) stands out in 18 papers. This combination allows the generation of user profiles through demographic data while studying their behaviour and making more precise recommendations for this specific segment. Knowledge-based filtering and collaborative filtering (KBF and CF) is used in six articles reviewed. The use of this technique is very useful when consumers' preferences are not known; thus, KBF filters based on the information available and CF uses information from similar profiles to make personalised recommendations for new consumers [14,25,50,61]. The literature review has also identified that studies have currently been developed that employ filtering techniques that combine more than two techniques, thus combining KBF, CF, and DF [78] and CF, CBF, and KBF [14,30,33,59].

4.4. Usage of Recommender Systems Pertaining to Application Areas in Smart Cities

Table 1 presents the use of filtering techniques pertaining to application areas in smart cities. The numbers represent the articles found in each area and filtering technique. The most used filtering technique in the area of mobility and transport (13 papers) is hybrid filtering combining DF and CF. The areas that have been developed using more filtering techniques are cultural heritage and tourism and urban innovation, which have used seven types of filtering techniques each. The most used technique is collaborative filtering, which is most developed in the area of e-commerce, with six studies, followed by urban innovation, with five studies.

This section offers a transversal review of the development of smart cities in the different application areas with the filtering techniques used to make the recommendations that have contributed to this development. The most widely used technique within the area of tourism is collaborative filtering, which uses the information and collaboration of city residents and visitors to improve the tourism experience [32,54]. Smart cities collect relevant tourist information, such as their preferences, tastes, and past activities. This information is obtained through sensors, mobile devices, and social networks. Then, this information is analysed and used to recommend tourist activities, places, and events to visitors. These recommendations are tailored to each tourist based on their interests and preferences [28] so that tourists can interact with other residents and visitors to get personalised recommendations. This is achieved through collaborative platforms and social networks, where tourists can share their experiences and receive advice from people who have already been to the same places [90,91].

Another important application area in a smart cities is mobility and transportation. Within these studies, the use of the hybrid filtering technique that combines CF and KBF stands out. Collaborative filtering in this context refers to a system that collects information and feedback from multiple sources, such as public transport users, drivers, transit authorities, and other relevant entities [70], such that the information is used to make informed decisions and continuously improve the mobility and transportation system in the city. KBF uses advanced algorithms and technologies, such as machine learning or big data analytics, to analyse and process large amounts of mobility and transportation-related information. This helps to identify patterns, trends, and problems and provides recommendations to optimise traffic flows, reduce congestion, and improve the efficiency of the overall transportation system [29]. In this sense, according to Pharm V. et al. [62], the mobility and transportation area in a smart city can take advantage of these collaborative filtering and knowledge tools as hybrid filtering in several ways:

- Data Collection: Sensors, mobile applications, and other sources can be used to collect real-time information on traffic, public transport, road infrastructure, weather conditions, etc. This information can be very useful for identifying patterns and trends and making informed traffic management decisions.
- Data Analysis and Processing: Advanced algorithms and technologies are used to analyse and process large amounts of collected data [95]. This helps to identify problems and opportunities for improvement in the transportation system, such as inefficient bus routes, recurrent congestion in certain areas, or the need to expand road infrastructure [96].
- Public Transport Optimisation: Through data analysis and user feedback, informed decisions can be made on public transport optimisation, e.g., bus frequency can be adjusted based on actual demand, routes can be reorganised to be more efficient, or accessibility and safety at stops can be improved [93].
- Road Infrastructure Planning: The CF and KBF can also help in the planning and design of road infrastructure. Information collected on traffic, vehicle flows, and user

needs can be used to identify areas for road improvement, create new roadways, or establish sustainable road infrastructure projects [50,96].

Table 1. Usage frequency of recommender systems in smart city application areas.

Aplication Domain/Filtering Techniques	Collaborative Filtering	Content-Based Filtering	Demographic Filtering	Knowledge-Based Filtering	Hybrid Filtering; DF & CBF	Hybrid Filtering; DF & CF	Hybrid Filtering; DF & KBF	Hybrid Filtering; KBF & CF	Hybrid Filtering; KBF, DF & CF	Hybrid Filtering; CF & CBF	Hybrid Filtering; CF, CBF & KBF
Cultural heritage & Tourism	3	1	2		1	2	1			1	
E-Commerce	6	2	1								
Economy	1										
Education								1			
E-governance	2										1
Energy management	4			2		1				1	
Gastronomy				1							
Geolocation	1					1					
Health	1			2							
Mobility & Transport	4		5			13		2	1		
Security	1			2							
Urban innovation	5	1		2	1	1		3		3	

The studies reviewed show that using a recommender system technique may be more appropriate depending on the type of recommendation sought and the application area within the smart city.

5. Conclusions

Smart cities are experiencing accelerated growth by and for the benefit of citizens. Therefore, it is essential to learn how smart cities work. Furthermore, recommender systems are highly valued because they allow using this collected data to provide personalised and useful information to the city inhabitants. These systems use algorithms and artificial intelligence techniques to analyse the data and offer recommendations and suggestions about different services and activities in the city. The growing use of applications also allows citizens to actively participate in decision making and contribute to the city's development. This is possible thanks to the use of a digital infrastructure that connects systems and devices in the city, collecting and processing data in real time to offer intelligent services and improve citizens' quality of life. Finally, recommender system filters make it possible to select, sort, and personalise recommendations, improve the accuracy of recommendations, and eliminate unwanted elements, thus providing a more relevant and tailored recommendation experience for each user. Therefore, smart cities and recommender systems work together to improve the quality of life of inhabitants, offering personalised and efficient services based on real-time data analysis. This allows citizens to make informed decisions and facilitates the efficient management of city resources and services. The field of application of recommender systems in smart cities promises significant transformations, with vast potential yet to be explored. This review provides essential guidance, identifying trends, challenges, and opportunities in this dynamic field. This analysis, we trust, will be a valuable tool for researchers, serving as a beacon highlighting promising directions and key areas for future exploration. With a solid foundation in place, we hope that this review will inspire continued progress, carrying with it the promise of optimising efficiency and quality of life in smart cities through the strategic application of recommender systems.

6. Limitations

One of the study's limitations is the sample size, particularly notable due to the theoretical nature of the data, necessitating comparison with empirical evidence. Additionally, this paper's research could be broadened to encompass the management of recommender systems, incorporating a comparative analysis of alternative optimisation algorithms. Another limitation of this study is that it only considered articles available in full text.

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