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# Contextual Suggestion and Recommendation Systems: A Review on Challenges in User Modeling and Privacy Concern

*Sistem Kontekstual Cadangan dan Syor: Satu Tinjauan Terhadap Cabaran dalam Pemodelan Pengguna dan Masalah Privasi*

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**Abstract**

The contextual suggestion systems are emerging as modified recommendation systems integrated with information retrieval techniques to search within large databases with the purpose to provide a user with a list of suggestions based on context i.e. location, time of the day, any day of the week (weekdays or weekend). The goal of this research is to conduct a systematic review in the field of contextual suggestion and recommendation systems incorporate with smart cities as the repositories of large datasets. This paper highlights the concerns linked with approaches being used in the contextual suggestion system and discussing various approaches which are being utilized in the contextual suggestion system. The keywords for query searching include; “contextual suggestion”, “recommendation system” and “smart city” which identified 191 papers published from 2012 to 2020. Four major article repositories were considered for searching (i) Science Direct, (ii) Scopus, (iii) IEEE, and (iv) Web of Science. The review was conducted under the protocols of four phases (i) Query searching in major article’s repositories, (ii) remove duplicates, (iii) scan title and abstract, and (iv) complete article reading. To identify the gaps in ongoing research a taxonomy analysis was exemplified into categories which further divided into subcategories, the main categories are highlighted as (i) review articles, (ii) model/framework and, (iii) smart city and applications. The critical analysis highlighted the limitations of approaches being used in the field and discussed the challenges. The review also reveals that most researches utilized approaches based on content-based filtering, collaborative filtering, preference-based product ranking, language modelling, evaluation measures were precision, normalized discounted cumulative, mean reciprocal rank, and the test collection comprised of internet resources.

**Keywords:** contextual suggestion system, recommendation system, smart city.

## INTRODUCTION

This research focuses to explore techniques subjective to contextual suggestion to make a system that can suggest a list of venues to a traveller to enhance travellers' experience. The main purpose of this study to neutralize techniques based on Information Retrieval (IR) and Artificial Intelligence (AI) which must have an ability to respond and make suggestions with the appropriate information as per the needs of the user. This system can benefit travellers interested in a list of venus based which would be based on context and their travellers' interests and personal preferences. In this paper, a systematic review has been done with the focus on contextual suggestion system and recommendation system aim to identify, evaluate, and summarize the findings of all relevant individual studies thereby making the available evidence more accessible to deliver a meticulous summary of all the available primary research.

Travellers depend heavily on their cell phones when they are searching for events to take part in, looking for fascinating close by venues or things to do. To understand the concept, for instance, a traveller explores a city, a set of interests are given for activities and places he visits while staying at the home city, on account to his interest a set of places and activities would be suggested by the system during his visit to the new city.

For instance, a user drinks coffee the system may suggest him a brand of coffee that he drinks and suggest the nearest locations for the stores where the specific brand of coffee is available, the user profile for this user is to drink coffee and more specifically is Lattee. When he travelled to Tanjong Malim, the Contextual Suggestion System can provide a list of the coffee shops. But the top list of the result is the coffee shops that do sell Lattee. The user profile may collect from the places that he has been visited by taking personal likes and dislikes for a place, past checked-in places and contextual aspects like user's current location and time of the day and week into an account, utilizing the various resources of data available in the repositories of the smart city. In comparison to other conventional recommender systems, this idea might be an ideal fit to make a list of suggestion within the context. The ultimate purpose of this study is to develop a precise contextual suggestion system that could be beneficial for a traveller and tourism.

Tourism in recent time has been evolving with technology which is bringing major restructurings to both the tourism industry and our view on tourism. Gradually, the critical role is played by Information and Communication Technologies (ICT) in offering competitiveness to the tourism industry and destination planning, therefore, evolving tourist's behaviour and tourism industry. Facebook, Twitter and YouTube, and other social media platforms presence are being felt in the tourism industry as the exponential growth has been witnessed in terms of user interaction on social media platforms. Google survey reported that travellers are getting influenced through the social network in the phase of travel planning at about 40%. While 50% of travellers plan their trip based on public reviews and experiences about the specific destination. Travel bloggers develop trust through interaction with followers and readers via social media, provide a recommendation based on their personal experiences about a place and ask for a tour recommendation for place and personal experiences from public International IPK

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(2012). Moreover, many location-based social networks such as; TripAdvisor, Yelp, Foursquare, and so on have emerged to fill the need for e-tourism. ICT is getting evolve further with the Internet of things and smart cities facilitate the modification of search engines, with the capacity and speed of searching techniques it needs to extract data from millions of documents. While technologies are continuously evolving it might be beneficial for tourism industries and tourist as well if a system would help in planning a tour or recommends a list of places automatically to a user based on the user's personal preferences and the system can facilitate millions of travellers around the globe to utilize the technology based on tour planning and automatic place's suggestion they would like to visit to enhance their travelling experience.

To develop such system, we need to re-investigate the query searching system to manage multifarious information with extremely contextual-based data with regards to user's data and interests. Second Strategic Workshop on Information Retrieval reported that in the future retrieval systems must be able to anticipate the contextual factors and respond with regards to user's needs and personal interests without asking the user to provide explicit data. For mobiles, such systems can be built like an app with features that makes interesting suggestions for places based on the current location of the user, personal interests, history of check-ins, and taking contextual factors into an account such as weather and time with no explicit query required. (Allan, Croft, Moffat, Sanderson, & Aslam et al., 2012), although several studies have been done to develop such systems, progressing towards the way to put the concept into practice.

This contextual suggestion system falls somewhere between traditional information retrieval and traditional recommendation. Unlike traditional information retrieval, the query is fixed ("entertain me", with the search results varying only to reflect the traveller's profile and the geo-temporal context. Unlike traditional recommendation systems, the range of suggestions is completely open, with the quality of the description forming an important aspect of the user experience. Ideally, this description would be modified based on the personal preferences of the traveller ((Dean-hall, 2014).

In comparison with the recommender system, the contextual suggestion system must synthesize data from various sources and should be precise for making suggestions based on the implicit query without given any explicit data. There is no explicit query, the default implicit query is: "Here I am, what should I do"? Here the contextual suggestion system would suggest a list of places to the user considering a context (i.e., location), as well as user interests via personal preferences and history (profile). As shown in Figure 1, where context consists of a user location, time of day (morning, afternoon, or evening), week (weekday or weekend), year (spring, summer, fall or winter), public holidays (i.e. Christmas or Halloween) weather conditions and so on. User's preferences were compiled into profiles that indicate preferences of a user for a particular attraction and it consists of ratings, endorsements, age, and gender. The suggestions are the list of places with descriptions that are anticipated by the system for a user who may find those places interesting to visit.

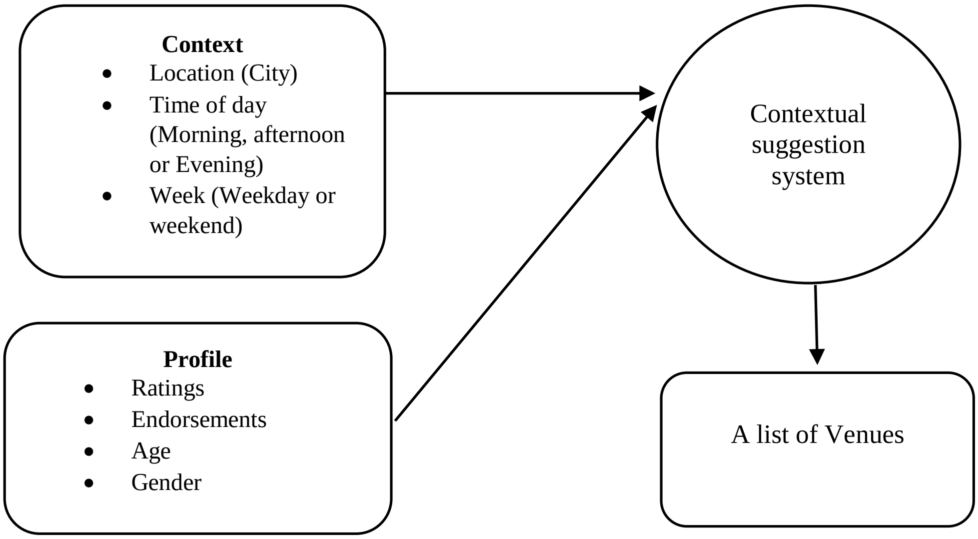


**Figure 1:** Contextual Suggestion System

The systematic review started with the deep query searching into the online article resources to compile all papers related to the area. The principle keywords utilized to represent the main areas are "recommendation system", "contextual suggestion system" and "smart cities". This incorporates any methodologies been used for “recommendation and contextual suggestion system by utilizing the database archives smart city offers” in different fields. The query was restricted to the articles written in English. Source articles were directed from four major digital databases. The first database is Science Direct. Science Direct is a site that offers access to a database of scientific studies specifically medical, technical, and other areas of research databases. The second database is Web of Science is another database utilized in this study which is an online membership/subscription-based site that gives multiple access to numerous databases for the search of queries linked with Science, Social Science, art, philosophy of nature, and humanity, however, it can retrieve only four papers related with the query. Another database is Scopus. Scopus is highlighting modified works with abstracts and citations for educational journals, scientific journals, books, and court procedures. The database also contains overall research identified with medication, science, innovation and technology, sociologies, arts, and humanities. The rationale for selecting the source databases because it provides access to the fields of science, social sciences, humanities, engineering, and technology in terms of the technical, theoretical and disciplinary effort of researchers around the world. The selection process consists of the study of literature followed by screening and filtering. The first phase was to scan the titles and abstracts to exclude duplicate resources and unrelated. The second iteration is through the reading of the articles obtained. The rest of the phases in conducting the review phase were summarized under review protocol and taxonomy analysis. The results of the systemic review were reported in the format either in the section of the thesis or in the journal paper. All insights are summarized under critical review discussions.

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**BACKGROUND OF THE STUDY**

A suggestion system based on contextual factors and personal interests has been the focus of several researchers. (Braunhofer, Elahi, Ricci, & Schievenin, 2013) worked on an application to make a list of venues to suggest to a user within the current city. This application is based on an explicit feedback query that asks quite a few questions related to the user's interests then prepared a list of venues based on their responses. (Adomavicius, Mobasher, Ricci, & Tuzhilin, 2011) utilized the collaborative filtering approach, incorporate it with contextual factors i.e. weather, time of a day, and days of the week (weekdays or weekend). (Baltrunas, Ludwig, Peer, & Ricci, 2012)) focused on budget and familiarity a user has within a city as contextual information. Regardless of these underway researches, it is always being a challenge to compare approaches to suggest a list of venues considering contextual factors, in regards to evaluation measures every team of researchers had considered their way of evaluation and methods for comparison, with no standard test collection was available for testing approaches and robust experiments.

Therefore, to standardized, the work based on contextual suggestion system the Text Retrieval Conference (TREC) has been conducting a workshop named Contextual Suggestion Track every year where they aimed to encourage teams around the globe for research on contextual suggestion system by providing a test collection to run experiments and with standard evaluation protocols for comparison. Every year participants perform a given task. The basic task is to consider the description of venues and contexts to anticipate suggestions for each blend of profile and context to make a list of venues a user might like to visit. Most of the participants gathered the dataset from the open web and other resources which was declared as standard test collection later on.

The purpose of the TREC Contextual Suggestion Track is to ease the process for future researchers by providing the standard tools to test the approaches and published approaches for comparison by adopting standard evaluation measures. Track participants have been exploring a large number of approaches every year. The basic approach is to compare a list of venues by targeting a city alongside ratings for venues against the user's personal preferences and the context to rank the list of suggestions. A variation of approaches was used for comparison, some approaches were based on positive ratings integrated with the textual similarity between the venue's profile and the user's profile (Dean-hall, Clarke, Kamps, Thomas, & Voorhees, 2012; Dean-hall, Thomas, Clarke, Simone, & Voorhees, 2013). Other approaches are based on reviews, ratings, categories of venues, and the contextual factors (Dean-Hall, Clarke, & Kamps, 2012; Dean-hall, Clarke, Kamps, Thomas, & Voorhees, 2015; Dean-hall, Clarke, Thomas, & Voorhees, 2014).

## REVIEW PROTOCOL

Reviews are planned to choose and assess the finding on a particular field of intrigue, in this context some pre-defined phases should be followed. Therefore, we orderly complete this systematic review according to the methodology prescribed by (Kitchenham & Charters, 2007). One of the objects of this study is to outline the current state of the art of contextual suggestions and recommender systems by performing a comprehensive inquiry of papers and revealing our fundamental outcomes and discoveries.

### Inclusion Criteria

In this review, the accompanying criteria are utilized to choose the possibly relevant records.

i. Contextual suggestion system is a quite recent area for studies, therefore papers published from 2012 are used in this research.

ii. Conference proceedings, unpublished work, doctoral thesis, blogs, and articles on electronic media and non-English studies are excluded in the review.

iii. Papers that only propose contextual suggestion and recommendation systems' "models" and "techniques" are screened for this study.

As appeared in Figure 2, we applied a multi-level method to filter the articles for our study. For query searching following keywords were utilized ("Recommending" OR "Recommendation System" OR "Recommendation" AND "Contextual" OR "Context" OR "Contextual Suggestion" OR "Contextual Suggestion System" AND "Smart City" OR "Smart Cities"). To start with, we indexed four online databases, Science Direct, Web of Science, IEEE, and Scopus in which we found 989 records after limiting search criteria to meet inclusion criteria. For our systematic review appeared in Fig. 1 for further screening. For sure keywords, titles, and abstract was examined in the initial step to minimize the irrelevancy of articles, 789 records were excluded in this step. Subsequently, we have examined duplicates from 268 remaining records, only five duplications were found. Next, 191 articles were found after full-text reading that meets the inclusion criteria. In the end, we only chose papers that are much subjected to the contextual suggestion systems and recommendations system for our review.

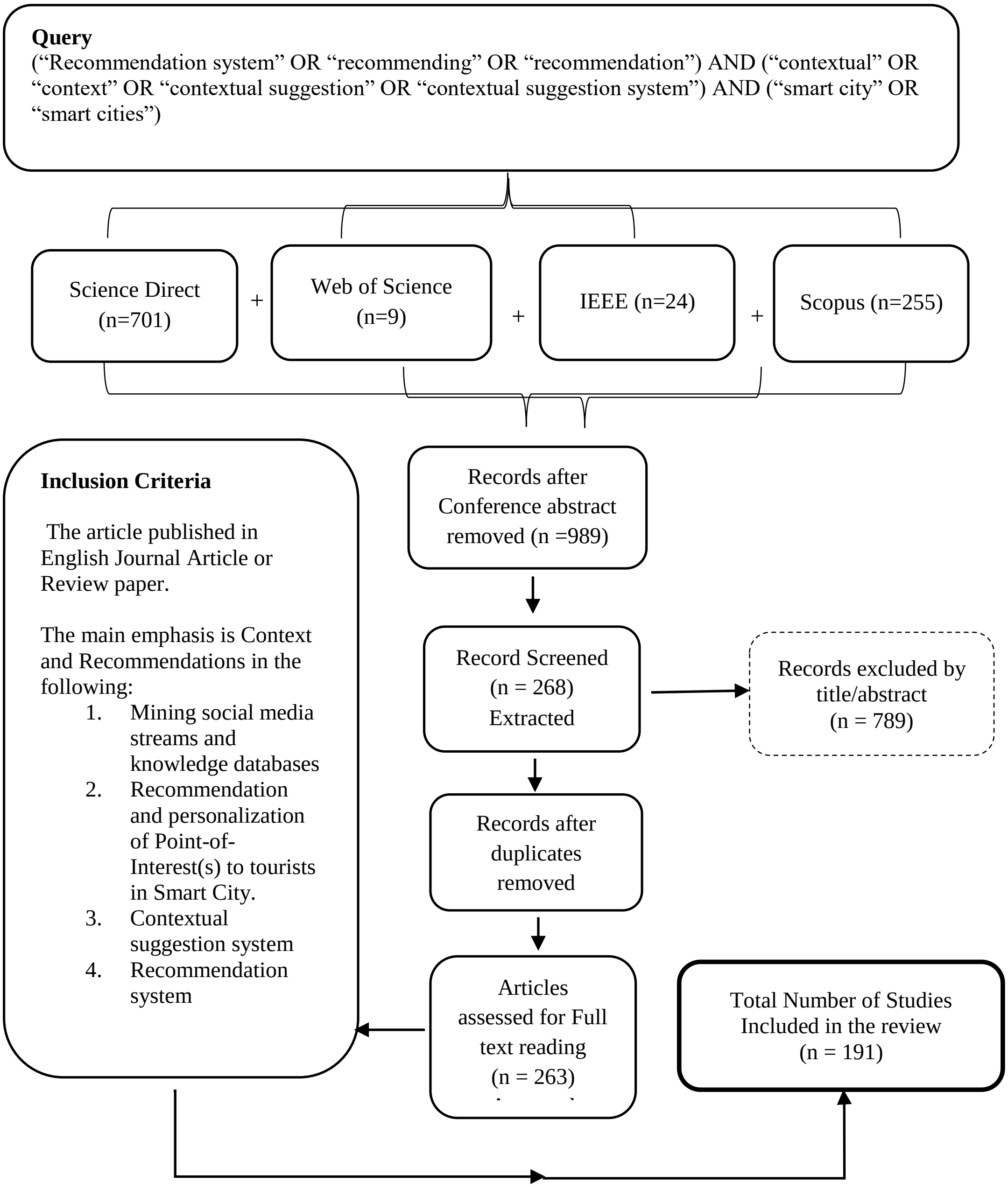


**Figure 2:** Flowchart of study selection, counting the search query and inclusion criteria

## TAXONOMY ANALYSIS

The total number of articles found in the four databases were 989 articles. Each database has a different query searching mechanism for searching articles, in each database the number of articles found; 701 from Science Direct, 24 from IEEE Explore, 9 papers from WoS, and 255 papers from Scopus. Specified the yearly trend from 2012 to 2020 shown in Figure 2. After skimming the titles and abstracts, resulting in 268 papers. The Full-text reading omitted 77 articles, leaving 191 articles as an ultimate set. Those papers were read carefully for the main purpose of discovering a general map to lead the research on the Contextual Suggestion System. We practical these outlines captured the common classifications of research articles and then refined the classification into the literature classification shown in Figure 5, it can be distinguished several subclasses in the main layers, although overlap occurs. In the following sections, we list the classifications that have been detected, constructing simple indicators all through the discussion.

Figure 4 shows the bar chart based on the number of articles by different categories in the digital databases. The number of articles used as literature was also categorized according to the field of study. Figure 3 shows the number of articles based on categories.

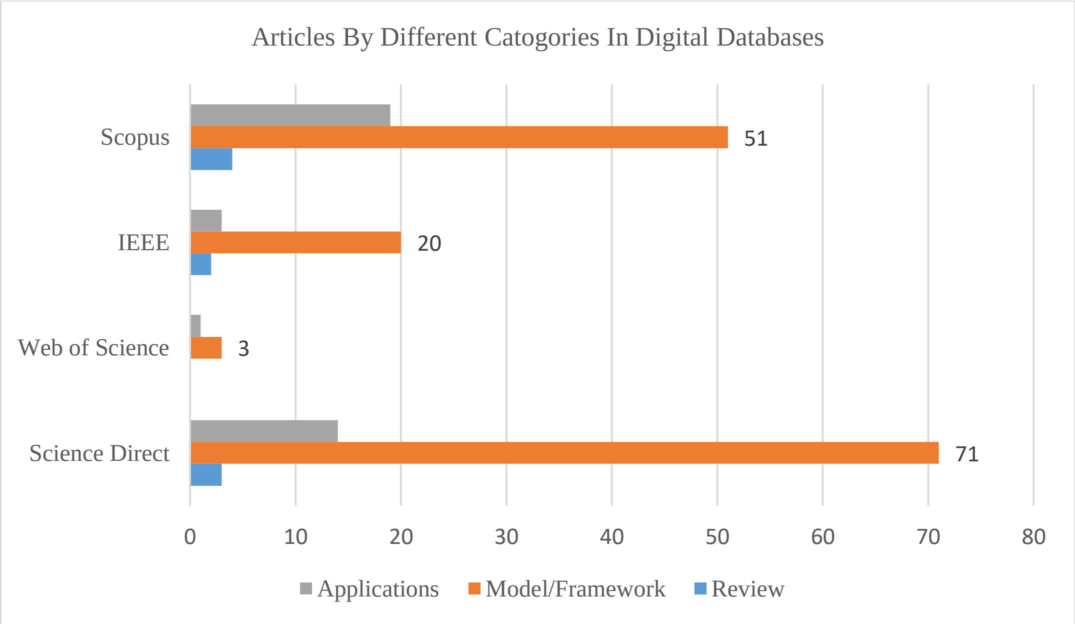


**Figure 3:** Bar Chart of Summarization Number of Articles by Different Categories

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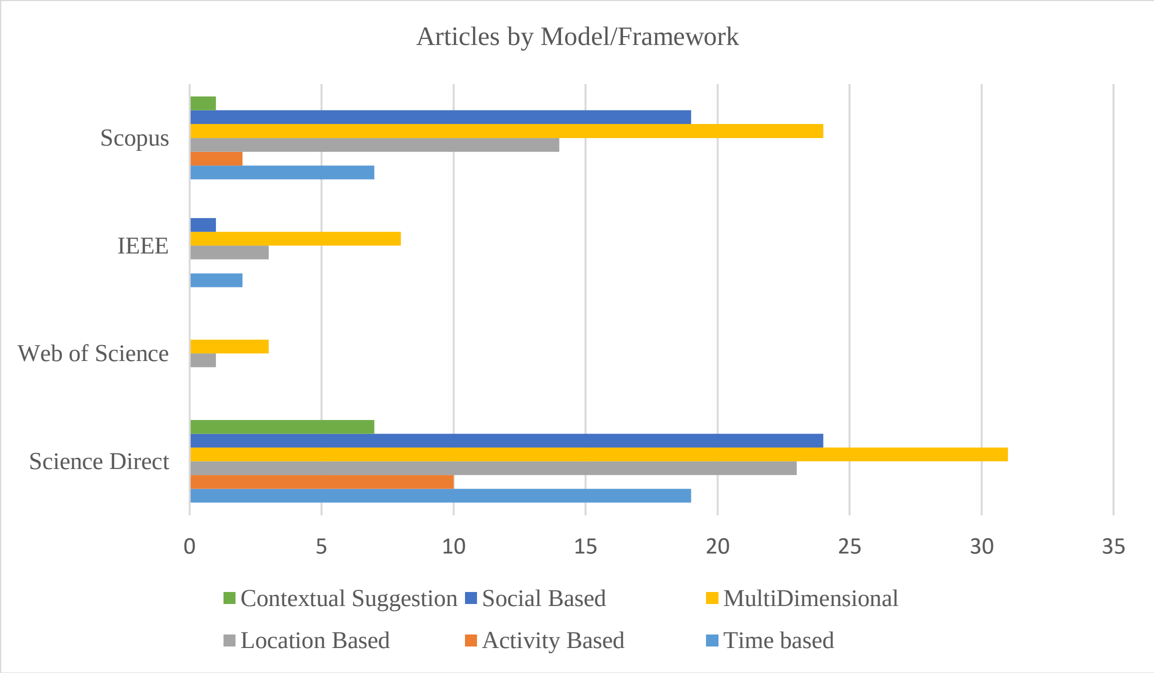


**Figure 4:** Bar Chart of Summarization Number of Articles by Model/Framework

From the overview of research articles, the results show a pattern of articles category. These articles are categorized according to the taxonomic literature as shown in Figure 6. The main focus of this research is on contextual suggestion and recommendation systems. The category of the articles decomposed into several sub-categories from the 4 main classes which are review articles, model/framework, dataset, and applications.

Overall, the review article is a summary of the current understanding or formulation of previously published studies related to the subject or topic of the study. Through review articles, new researchers can identify several new findings, progress, gaps in research, and people involved, debated about some issues and new ideas that can be highlighted for future research.

Model/framework is one of the methods of effective research that consists of real or abstract forms such as mathematical formulas. The model/framework in this research was divided into further six categories which are based on temporal information, human activities, user geographic position captures from GPS, content-based which represents a user in an unfamiliar area, multidimensional (combination of all the model/framework), and contextual suggestion which is based on context. The model/framework is a combination of approaches used in the development of a contextual suggestion or recommendation system which is further discussed in location-based and categories in different techniques used in the development of location-based contextual suggestion and recommendation system (closely related to travelling and venue suggestions).

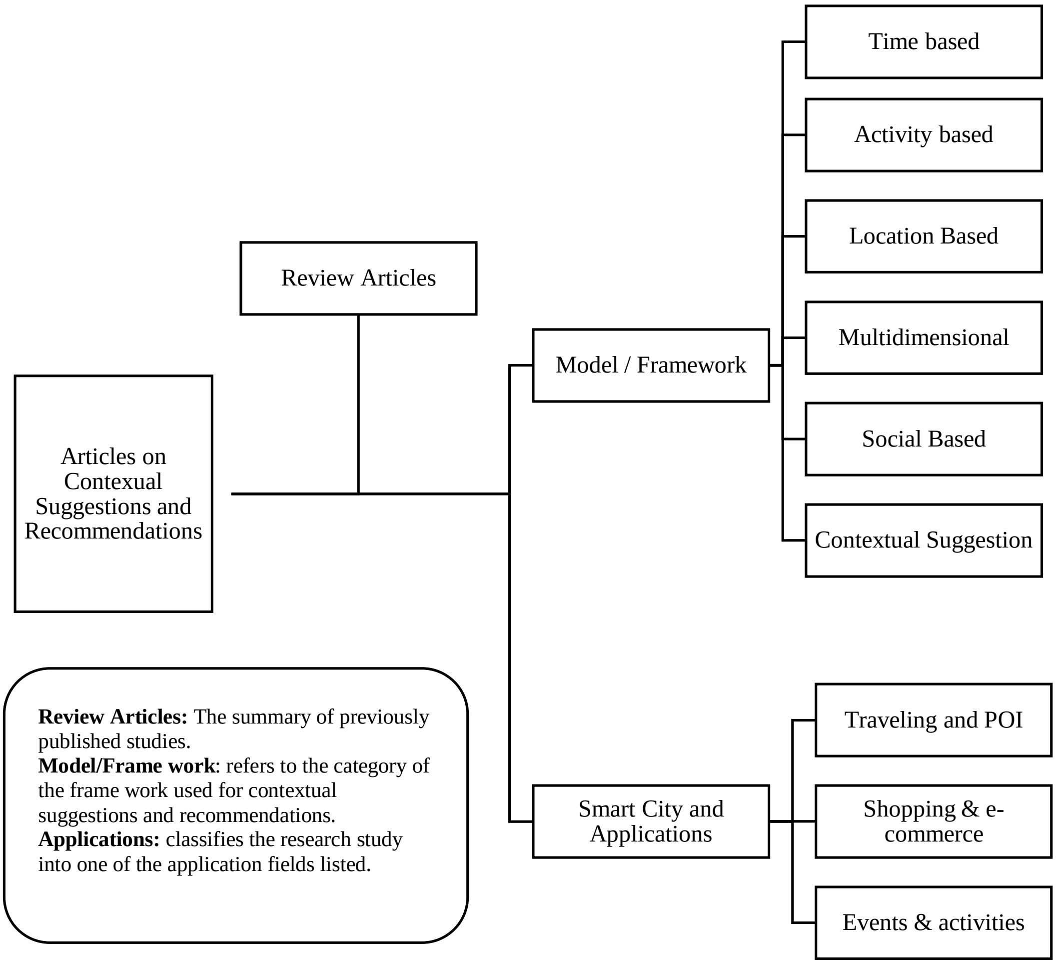


**Figure 5:** Literature Classification of Contextual Suggestion System and Recommendation System

Smart City and Applications category in this study is defined as the initial prototype of the existing approaches used in the development of the system into an application. This category is further divided into travelling and point of interest (POI), shopping/e-commerce, and events/activities.

## CRITICAL REVIEW

This section discusses the review on critical recommendation and contextual suggestion systems' studies conducted by previous researchers. Numerous studies have been found in the field of recommendation systems but the review founds that not many studies are available with the focus on contextual suggestions. In terms of approaches, most of the studies based on recommendation system used explicit feedback for data and crawled the data from internet resources to test the approaches and contextual suggestions system were based on both explicit feedback, implicit feedback incorporate with contextual factors moreover some studies found which utilized the set of test collection provided by TREC Contextual Suggestion Track, besides, some of the researchers used a crawler to extract information from internet sources for further enhancements. The review also reveals that most researches utilized approaches based on content-based filtering, collaborative filtering, preference-based product ranking, language modelling, evaluation measures were precision, normalized discounted cumulative, mean reciprocal rank, and the test collection comprised of internet resources.

Out of 191 articles, there were only 41 articles found which focused on location-based recommendation system and contextual suggestion system, most of the studies used content-based filtering approach however it considers as unfit since it does not facilitates venue ratings whether negative or positive which is one of the limitations (Rikitianskii, Harvey, & Crestani, 2014). Some researches utilized rating-based collaborative filtering based on factorization machine to process the user's feedback and contextual information to improve the accuracy of suggestions, however, it compromises with data sparsity problem where the suggestion suffers from the accuracy (Cheng, Yang, King, & Lyu, 2012; Griesner, Paristech, & Naacke, 2015).

In several pieces of studies preference-based product ranking technique and weighted and unweight combination of the attributes belong to users was utilized, where the attributes such as prices, and reviews of the venues were taken for preference-based ranking and those attributes which signify how likely the user's behaviour gets influenced and how likely it is if a user visits the particular suggested venue, however, it suffers from lack of feedback, and there are no such parameters which evaluate the behaviour of the user, therefore such approaches lack data and cannot be useful for venue recommendations and contextual suggestions scenario (Hariri, Mobasher, Burke, & Zheng, 2010; McCreadie, Mackie, & Manotumruksa, 2015). Few researchers utilized review based approaches but suffered from a lack of reviews available for some of the venues (Chen & Chen, 2014; Chen, Chen, & Wang, 2015; Cheng et al., 2012; Garcia Esparza, Mahony, & Smyth, 2010; Griesner et al., 2015; Hariri et al., 2010; McCreadie et al., 2015; Rikitianskii et al., 2014; Tan, Khan, & Lim, 2018; Yang & Fang, 2015)

## CHALLENGES

The recommendation system is an area of AI that recommends contents according to user data, while the contextual suggestion task falls somewhere between traditional information retrieval and traditional recommendation. This approach is required in designing a better system that can suggest any kind of content with context, either movie, music, shopping, and e-commerce, or travel. However, here, the focus of discussion is e-tourism, venue suggestions, and respective challenges other researchers face in the development of contextual suggestion systems.

### Concern on the Data Set

One of the primary attributes of smart cities is that the richness of sensors allows the flow of real-time data associated with the Internet of things (IoT) and provides a deep insight into the current situation of the city. The sensors include social (e.g., Social Media), physical (e.g., CCTV cameras), and even weather sensors, all connected to the IoT. However, utilizing this huge amount of data repositories that smart cities offered remains a challenge. Subsequently, this sub-section discusses challenges related to the datasets used in previous studies and overall challenges in creating dataset repositories.

At present, LBSNs (Massai, Nesi, & Pantaleo, 2019; Ye, Xiong, Li, Gao, & Xu, 2019) such as Foursquare, Yelp, and Google places are being used to extract data for venue recommendation and contextual suggestion systems. LBSNs allow users to broadcast their current location, which can be shared with friends and other users, and provide their views based on experience in terms of ratings and venue comments.

TREC dataset (Arampatzis & Kalamatianos, 2018) lacks user demographic information and social situations (Aliannejadi & Crestani, 2018; Sappelli & Kraaij, 2018), which limits research options to content-based recommendation approaches that use only available information. Subsequently, content-based approach (Aliannejadi & Crestani, 2018) is adopted since developers gain control over the suggested information by utilizing customized dataset content that prevents extracting rich tourist content available on LBSNs (Chakraborty, 2018; Cheng, Liu, & Yu, 2016; Yang, Wang, Fang, & Cai, 2015). To increase accuracy, several approaches are based on implicit feedback that requires users to grant access to personal information or explicit feedback that provides personal preferences for venues (Aliannejadi & Crestani, 2018; Chakraborty, 2018; Crestani, 2016; Guo, Zhu, Xu, Shang, & Ding, 2016; Jing, Hu, & Wei, 2015; Palaiokrassas, Charlaftis, Litke, & Varvarigou, 2017; Xu, 2014).

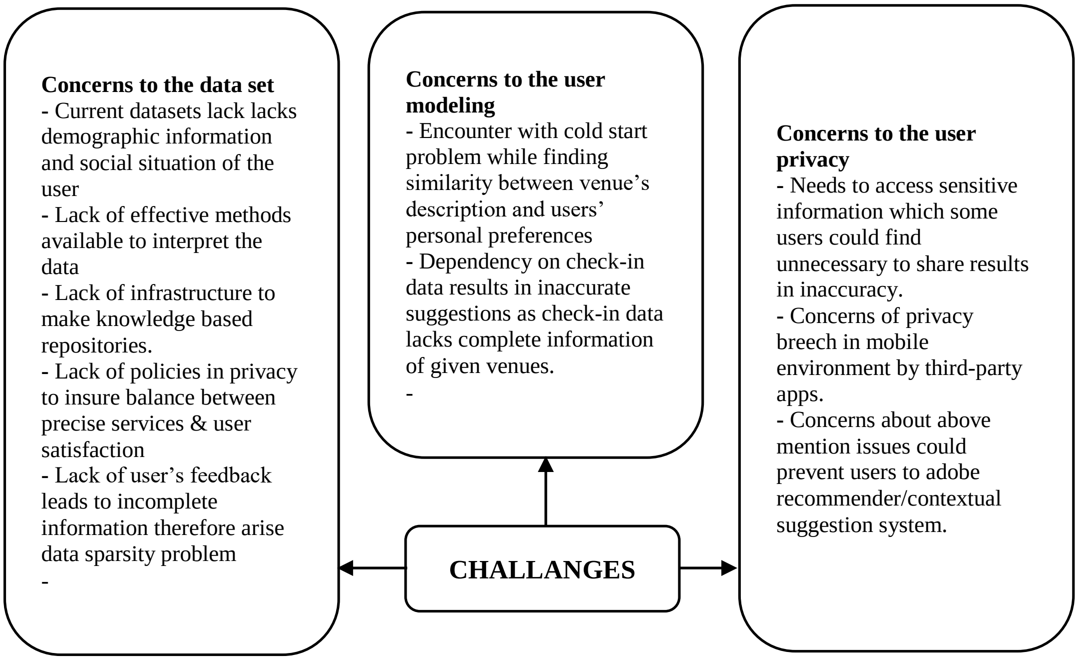


**Figure 6:** Challenges

Concerns arise about the lack of effective methods, to interpret the data and generate useful information for a user from the bulk of raw data repositories. To store such huge knowledge-based repositories extracted from physical sensors, lack of physical infrastructure with no standard policies raise ethical issues where special attention should be paid to ensure passable equilibrium between value-added services and user satisfaction.

Another challenge (Aliannejadi & Crestani, 2018), is data sparsity in venue suggestion and recommendation systems. A large number of venues with the considerable variety available on LBSNs contrast with limited user exposure to locations, resulting in a lack of feedback available (i.e., reviews and ratings) for several venues. Hence, the incomplete information increases the difficulty to utilize the study (Zhang et al., 2019). Subsequently, data sparsity arises in the user-item matrix based on collaborative filtering approaches (Bianchini, Antonellis, Franceschi, & Melchiori, 2017; Cheng et al., 2016; Deveaud et al., 2014; Guo, Li, & Lu, 2017; Hashemi & Kamps, 2017; Kiseleva & Kamps, 2014; Ren et al., 2018).

### Concern on the User Modelling

In recommendation and contextual suggestion systems, modelling a user profile based on personal information (activities and personal preferences) and reviews based on the last visited venue is one of the challenges (Yang, Korayem, AlJadda, Grainger, & Natarajan, 2017). Therefore, finding similarities

(Sánchez & Bellogín, 2019) between venue description and user personal preferences to create a list of suggestions may lead to the cold-start problem (Gazdar & Hidri, 2020; Rikitianski et al., 2014). The same problem (Yang et al., 2015) is encountered by giving leverage to the reviews and ratings extracted online and provided by users for a particular place. Approaches based on collaborative filtering. (Aliannejadi & Crestani, 2017; Aliannejadi, Mele, & Crestani, 2016; Hubert & Cabanac, 2012; Lu, Ioannidis, Bhagat, & Lakshmanan, 2014; Manotumruksa, Macdonald, & Ounis, 2019) also suffer from the cold-start due to the needs for sufficient user information to create recommendations (Tewari, Singh, & Barman, 2018), To learn the user personal preferences, these approaches mostly depend on check-in data (Aliannejadi & Crestani, 2018; Bao, Zheng, Wilkie, & Mokbel, 2015; McCreadie et al., 2015), which lacks complete information about a place to precisely anticipate user views for a specific venue.

### Concern on Privacy

Privacy issues are additional concerns in this study given that the utilization of user information is being extracted from social media platforms to increase the accuracy of the recommendations. Moreover, existing recommendation services are required to store and manage user profiles to constantly increase the accuracy of recommendations (Dandekar, Fawaz, & Ioannidis, 2012; Rivero-Rodriguez, Pileggi, & Nykänen, 2016). However, user profiles comprise personal data, including sensitive information that users may be uncomfortable to share (Efraimidis, Drosatos, Arampatzis, Stamatelatos, & Athanasiadis, 2016; Masseno & Santos, 2018; Rivero-Rodriguez et al., 2016; Yargic & Bilge, 2019), This dichotomy creates an alarming situation for a potential user who is highly concerned about privacy breach through the use of recommendation service (Das, Pathak, Chuah, & Mohapatra, 2017; Zhu, Xiong, Ge, & Chen, 2014). Furthermore, the privacy issue is further aggravated when the profiles of diverse users are merged to magnify the effect of datasets to empower recommendations (Véras, Prota, Bispo, Prudêncio, & Ferraz, 2015). The wide range of sensitive data available to smartphones makes privacy issues even more severe for mobile recommendation systems. Smart mobile platforms provide easy access for apps to inaudibly upload personal data into remote servers or a cloud. User awareness for privacy concerns is acknowledged as one of the greatest obstacles that may prevent a user from adopting a contextual-based system or recommender-based services (Zoonen, 2016).

## PRACTICAL IMPLICATIONS

The benefits of a contextual suggestion system and recommendation system in various areas of the study clearly showed its importance in looking at potential based on certain indicators. This section discusses the benefits of this research in the field of tourism.

The information repositories available on the internet have seen an enormous increase in the users utilizing these sources in the past few years. The information may depend on the user's queries and the needs of information. For a traveller, the repositories can be useful when he/she is planning a trip to an unknown city. The associate information which a traveller looks for while planning a trip is mostly about accommodations, eating places, cultural activities, and historic places as compared to other terms. Despite this, the user is more likely to overwhelm by the list of results he gets from web search engines based on tourism sites, i.e. Trip Advisor. The process of evaluating the long list of results is time-consuming and could be complex for a user in order to choose the option which perfectly fits their needs.

Contextual-based personalization approaches can provide tailor-made information based on user's preferences, with restraints of a list of venues that are most relevant to the user, and the contextual suggestion systems and recommender systems should screen out irrelevant results to improve its accuracy. A travel-based contextual suggestion system can fulfil the required needs and ease the resources searching or places to choose for the traveller. These systems can utilize machine learning algorithms which could be useful when the system needs to analyze the personal preferences of the user through implicit or explicit feedback.

Moreover, these contextual suggestion systems may not only take the preferences into account but process the several contexts of the trip as well which can benefit a tourist when he/she is already at a new city and a change in circumstances can customize a whole trip in limited time by using mobile devices. The context can include location by default with a little change in context can change activities of a trip from a business trip to the relief of rest days and change in weather conditions. Approaches based on context can proactively notify a user with suggestions, with regards to the current context of the user. For instance, on a business trip when a location was planned for an office meeting if the meeting postpones a traveller can prefer to spend some time around the nearby places thereof the contextual suggestion system would provide a list of places according to the needs of the user in a particular context.

A tourist completely relies on mobile devices and this behaviour has been witnessed with the massive increase, therefore smart tourism applications provide a good opportunity for mobile services that help visitors by offering recommendations based on their preferences and their current context.

## CONCLUSION

Contextual suggestion and recommendation systems are widely used in various fields such as shopping & e-commerce, travelling and point of interest, events & activities, and social media. However, the systematic review conducted on literary studies found 41 out of 191 articles cover location-based approaches for contextual suggestion systems, 28 out of 191 articles were time-based, and 66 out of 191 were based on multi-dimensional approaches. 44 out of 191 focused on social-based recommendations and contextual suggestions, and the remaining 12 out of 191 articles discussed activity-based approaches. Most of the research (112/191 articles) were based on the analysis or evaluation study of model/framework, applications (70/191 articles), and reviews (9/191 articles).

The contextual suggestion systems and recommendation systems have become a phenomenon in certain areas of IR and AI is to help users to make strategic planning based on the factors like their interests and context that can influence their decision. This trend shows the several approaches used in the development of a recommendation system and contextual suggestion system providing a list of venues based on the context in line with the current technological developments and data resources available in smart cities. Researchers express their opinions and suggestions in their respective research papers to solve existing problems or challenges for future research references for the improvement process. Future researchers can refer to the diversity of data collection techniques, processing methods for approaches, and challenges in ranking the suggestions, as well as the entire work process on contextual suggestion system.

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