

A Survey on Point-of-Interest Recommendations Leveraging Heterogeneous Data

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Abstract

Tourism is an important application domain for recommender systems. In this domain, recommender systems are for example tasked with providing personalized recommendations for transportation, accommodation, points-of-interest (POIs), or tourism services. Among these tasks, in particular the problem of recommending POIs that are of likely interest to individual tourists has gained growing attention in recent years. Providing POI recommendations to tourists *during their trip* can however be especially challenging due to the variability of the users' context. With the rapid development of the Web and today's multitude of online services, vast amounts of data from various sources have become available, and these heterogeneous data sources represent a huge potential to better address the challenges of in-trip POI recommendation problems. In this work, we provide a comprehensive survey of published research on POI recommendation between 2017 and 2022 from the perspective of heterogeneous data sources. Specifically, we investigate which types of data are used in the literature and which technical approaches and evaluation methods are predominant. Among other aspects, we find that today's research works often focus on a narrow range of data sources, leaving great potential for future works that better utilize heterogeneous data sources and diverse data types for improved in-trip recommendations.

Keywords: Recommender Systems, Tourism, Point-of-Interest Recommendation, Heterogeneous Data

1 Introduction

Tourism is the act of traveling for pleasure or business to places outside one’s usual environment (Hamid et al, 2021). It includes a wide range of activities such as visiting tourist attractions, sightseeing, participating in cultural events and activities and exploring natural wonders. Based on the temporal sequence of tourism behavior, the tourism process can be divided into three distinct phases (Pearce, 2005): pre-trip, in-trip and post-trip, as depicted in Figure 1.

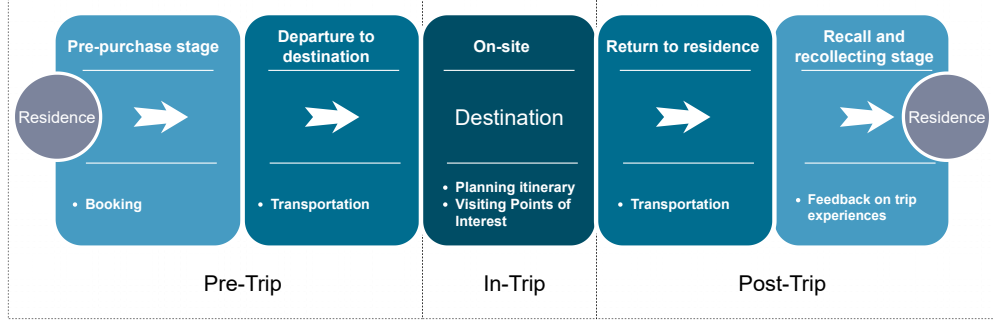


Fig. 1: Temporal Phases of the Tourism Process

Throughout these travel phases, the in-trip phase presents a more complicated situation compared to other phases because of the continuous changes in the contextual environment during the trip, which has a direct effect on tourists’ travel behavior, such as selecting different transportation modes, adjusting their visiting time or visiting different tourist attractions. Among the various aspects of in-trip planning, selecting appropriate POIs can be a significant challenge for travelers, since *point-of-interest* is a holistic concept that encompasses any places tourists can visit during their trip, including museums, parks, cinemas, art galleries, restaurants, coffee shops, shopping centers, etc. (Safavi et al, 2022). And it can be a time-consuming task for tourists to filter out relevant content from the vast amount of available information about POIs on the Internet.

In order to address these issues, information mechanisms are urgently needed in the tourism domain to assist users by making useful and effective suggestions from the plethora of available POI choices. Recommender Systems (RSs) are considered as established solutions for this task due to their ability to provide personalized recommendations based on various travel purposes and individual preferences. Being the primary task during the trip, offering POI recommendations may however face significant challenges in providing up-to-date recommendations based on tourists’ preferences and context (Wu et al, 2022). To achieve this, in-trip POI RSs require access to user-related data to understand their needs and preferences. Therefore, it is crucial to collect and analyze all kinds of available data in the tourism domain to offer valuable recommendations to visit POIs.

Tourists engage in various activities and interact with various elements throughout the duration of their trip. With the widespread use of smartphones and various online applications, a wealth of tourism-related information can be obtained from multiple data sources. These sources encompass descriptions and statistics related to tourism offers and marketing, as well as records of tourists’ feedback on consumption of tourism products and services (Yochum et al, 2020). Such information constitutes a fertile ground for investigating tourists’ preferences and behavior in the context of POI recommendation research. However, integrating the aforementioned data sources to address the recommendation challenges during trips poses significant difficulties due to their inherent heterogeneity, which manifests in a high variability in data types and formats (Wang, 2017).

These different types of data can exhibit heterogeneity from syntactic, conceptual, terminological, semiotic and other aspects due to the diverse demographic backgrounds (language, age, gender, etc.) of the data generators, the variety of data acquisition devices (mobile phones, computers, GPS devices, etc.) and the complexity of data types (text, images, videos, trajectories, etc.) (Jirkovský and Obitko, 2014). This issue is particularly prominent for RSs in the tourism domain, where it is challenging to integrate different types of data to establish a holistic user model. Therefore, data integration techniques that can effectively analyze and explore comprehensive data have become more important in recent years (Abassi et al, 2022). However, it is important to note that despite the potential benefits, the integration of heterogeneous data as input to POI RSs is still not widely employed and lacks a systematic and comprehensive overview of its utilization in the existing literature.

To bridge this gap, the contribution of this work is as follows:

- We conduct a systematic literature review spanning from 2017 to 2022. The review provides a comprehensive analysis of today’s state-of-the-art techniques, widely used data sources and popular evaluation metrics in the context of in-trip POI recommendations.
- We review the current utilization of heterogeneous data sources in the field of POI recommendation research. Our study offers valuable insights into the types of heterogeneous data that have been employed and sheds light on the integration techniques utilized in existing POI RSs.
- We identify and present potential research directions that can guide future work in the field of POI RSs. These research directions provide valuable insights and serve as a roadmap for researchers to explore novel approaches, address existing challenges, and advance the state-of-the-art in in-trip POI recommendation.

The rest of the paper is structured as follows: Section 2 provides background information and preliminaries about RSs in the POI recommendation domain; Section 3 describes the research methodology of our information-centric survey for in-trip POI RSs; Section 4 contains the main findings of this work; Section 5 outlines open gaps and future research opportunities; Section 6 concludes our analysis and offers remarks on future research directions.

2 Background and Preliminaries

In this section, we present an overview of the fundamental concepts associated with RSs and their specific application within the tourism domain. Furthermore, we provide a concise summary of past surveys conducted in the realm of POI recommendations, effectively elucidating the gaps and constraints inherent in the existing survey literature.

2.1 Recommender Systems and Their Applications in Tourism

RSs have become ubiquitous in various application domains today, and their origins can be traced back to the early 1990s, when they were first applied in experimental settings for personal email and information filtering (Jannach et al, 2021). Since then, they have become a common feature of many online platforms, serving as tools for helping users discover content that may be of interest to them. With the continual progress and evolution of recommender systems, an array of diverse system types has emerged. Among these, the most utilized types of recommendation systems comprise (Ricci et al, 2022): Collaborative Filtering (CF) methods, which suggest items based on the similarity of users’ past behaviors or preferences; Content-based (CB) methods, which suggest similar items to those that a user has previously liked or interacted with based on the characteristics of the items themselves; Hybrid methods, which integrate multiple techniques including those mentioned above as well as demographic-based, knowledge-based, and community-based methods to leverage the strengths of each approach and provide more accurate and diverse recommendations.

With the help of the aforementioned techniques, RSs have been extensively applied in various domains such as e-commerce (Salunke and Nichite, 2022), social media (Anandhan et al, 2022), entertainment (Schedl et al, 2022; Jayalakshmi et al, 2022), and education (Cui et al, 2018). As an important application, RSs in the tourism domain can recommend tourists the most appropriate transportation options (such as flights and trains), accommodations, POIs and other items that are necessary for their trip (Sarkar et al, 2022). Therefore, in the present era of information overload, there is an increasing demand for Tourism Recommender Systems (TRSs) to alleviate the time spent on information retrieval for travel. These systems are designed to reduce the time spent on retrieving travel information and can effectively assist users with a variety of tourism-related recommendations, as illustrated in Figure 2.

When examining the application of TRSs specifically in the domain of POI recommendations, it becomes apparent that data can be gathered throughout various stages of the trip, including tourism business transactions. Examples of such data are presented in Table 1 reflecting tourists’ preferences for POIs and providing valuable information for building effective in-trip POI RSs, as discussed in (Höpken and Fuchs, 2022). Aside from these data collected from tourism business transactions at each stage of the trip, there are other types of data that can be utilized to generate personalized recommendations. These include tourists’ demographic information and friendships from profiles on social media platforms (Kolahkaj et al, 2020; Cai et al, 2022), as well as basic information about tourism products and services, such as POI location, costs, facilities (Qomariyah and Kazakov, 2021), etc. Moreover, contextual

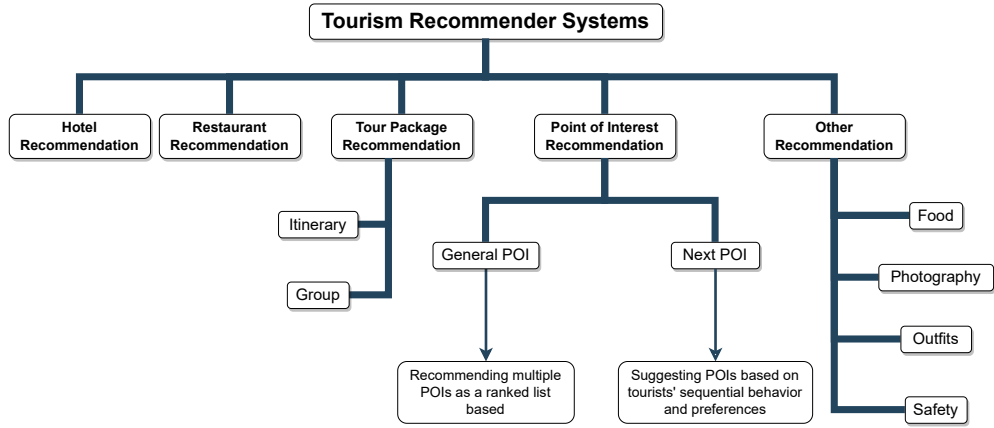


Fig. 2: Main Recommendation Tasks in Tourism

information about traffic and weather conditions during travel is being explored to build context-aware RS as well (Zhu et al, 2018; Hossain et al, 2022). By leveraging these diverse data types, POI RSs can generate personalized recommendations that align with the individual preferences and needs of tourists throughout their entire trip. The integration and analysis of these data sources hold the potential to enhance the accuracy and relevance of POI recommendations, ultimately enriching the overall travel experience for tourists.

Table 1: Data Sources for POI Recommendations at Different Trip Phases from Tourists' Business Transaction (Höpken and Fuchs, 2022)

Phase	Data	Source
Pre-trip	Descriptions and marketing statistics of tourism products or services	Official websites, marketing networks, search engines, social media platforms
	Information search records	Search engines, travel websites, mobile apps/guides, social media platforms
	Booking or reservation records	Booking systems
In-trip	Transportation trajectories and POI check-in records	Ticket systems, social media platforms
	Accommodation records	Accommodation providers, official statistics, mobile app usage
	Consumption records	Local ticket offices, tourists' payment systems
Post-trip	Feedback for tourism products	Online review sites, supplier-specific online feedback, survey systems, social media platforms

2.2 Previous Reviews on Point-of-Interest Recommendation

With an increasing emergence of research on POI RSs in recent years, a plethora of models have been proposed to tackle the problem of providing personalized POI recommendations. There have been several review articles highlighting the major findings and limitations from a certain perspective.

From the viewpoint of the data that are used for POI recommendations, [Yochum et al \(2020\)](#) conducted a survey on linked open data in location-based recommendation systems in the tourism domain, providing a systematic review and mapping of linked open data in location-based RSs in the tourism domain, summarizing the research achievements during 2001 and 2018 and providing a distribution of the different categories of location-based recommendation applications using linked open data. This survey also suggests possible future research directions for the use of linked open data in location-based recommendations for tourism. Another survey conducted by [Sánchez and Bellogín \(2022\)](#) delved into the domain of POI recommendation research spanning the period from 2011 to 2020, with a specific focus on the integration of data sourced from location-based social networks (LSBNs). The authors furnished an intricate analysis of diverse information sources, evaluation methodologies and algorithms within the context of POI recommendation and highlighted both the existing prospects and challenges that continue to persist within this field. Additionally, a comprehensive analysis of the effect of contextual factors, including social, temporal, spatial, and categorical factors on recommendation models was conducted by [Rahmani et al \(2022a\)](#). Through an extensive survey of context-aware location recommendation, they quantitatively evaluated the impact of these contextual factors on POI recommendations using both existing and novel linear/non-linear models. The surveys conducted by [Sánchez and Bellogín \(2022\)](#), [Rahmani et al \(2022a\)](#), and [Yochum et al \(2020\)](#) are closely related with our current study, as they have undertaken information-centric survey work in the domain of POI recommendation. In contrast to these works, our present survey is however not limited to specific types of information such as data from LBSNs or linked open data, but specifically analyzes the utilization of all kinds of data as input to POI recommender systems.

In the light of numerous POI recommendation techniques, a recent study by [Liu et al \(2017\)](#) provided an evaluation of twelve state-of-the-art POI recommendation models. Through this thorough evaluation, significant findings about the different model performances due to data, users or modeling methods were obtained, which can aid in the better understanding and utilization of POI recommendation models in various scenarios. Due to the surge of research activities utilizing deep learning paradigms in the field of POI recommendations, a survey of major deep learning-based POI recommendation works has been compiled by [Islam et al \(2022\)](#). This survey categorized and critically analyzed recent POI recommendation works based on different deep learning paradigms, as well as relevant features such as problem formulations, proposed techniques, and used datasets. Ultimately, the survey may serve as a valuable resource for researchers and practitioners to gain insights into current trends and future research directions in the area of POI RSs.

In another survey on POI recommendation research, [Werneck et al \(2021b\)](#) conducted a systematic overview of 74 relevant papers published from 2017 to 2019 and

proposed an extensible POI recommendation benchmark to address and identify limitations, including a prioritization of accuracy over other quality dimensions and a low intersection of metrics and datasets used to evaluate proposed solutions. In a subsequent work, Werneck et al (2022) developed a reproducibility framework based on Python software libraries and a Docker image to reproduce experimental evaluations on POI recommendations using different datasets, metrics, and baselines.

Despite the existence of prior surveys on POI recommendation research, a comprehensive, systematic and information-centric comparison that reflects the current state-of-the-art in the field is still lacking. Specifically, there is a need to investigate how recent research has utilized heterogeneous data sources and to provide an overview of the latest advancements in in-trip POI RSs. Such an overview should consider various aspects, including techniques, data and evaluations, which are the primary areas of focus of this work.

3 Research Methodology

This section outlines the research methodology adopted to conduct a systematic literature review and to gather relevant research papers for this study. The primary objective of this research is to offer a comprehensive overview of the most recent advancements in the realm of in-trip POI recommendations, specifically focusing on an information-centric perspective.

Definition of Research Questions. In order to achieve the stated objective, the following research questions (RQs) were formulated:

- **RQ1:** What is the current state of research on POI recommendations in terms of techniques, data and evaluation?
- **RQ2:** How are heterogeneous data currently being utilized in in-trip POI recommendation research?
- **RQ3:** What are the existing limitations and potential future directions for research and development of in-trip POI RSs?

Search Strategy. A systematic literature search was conducted in the DBLP database¹ to retrieve English-language journal citations published between 2017 and 2022. This time frame was selected to focus on recent research and minimize overlap with previous surveys on tourism RSs. The search strategy involved various search queries related to in-trip RS, with a particular emphasis on terms related to the concept of POI.

To ensure a comprehensive coverage of the search results, common prefixes were incorporated, such as the inclusion of terms like "recommend" for "recommender system" and "recommendation". Furthermore, synonymous terms for the keyword "POI" were included, such as "point-of-interest" and "attraction". The final search query was the following:

"recommend" AND ("point-of-interest" OR "POI" OR "tour" OR "activity" OR "attraction" OR "event" OR "venue")

¹<https://dblp.org/>

Through this search strategy, our aim was to capture a wide range of relevant literature related to RSs, particularly in the context of POI recommendations.

Screening of Papers. The inclusion criteria to select relevant papers for this study were defined as follows:

1. The paper is written in English.
2. The publication date of the paper falls between 2017 and 2022.
3. The journals in which the paper is published ranks in Q1 according to the Scimago Journal & Country Rank (SJR) for the publication year.
4. The paper is an original research article or review article related to general POI recommendation or the next-POI recommendation².

Exclusion criteria were also defined to exclude papers that do not meet the specific requirements of this study. Papers fulfilling the following criteria were excluded:

1. Papers that focus on POI recommendations for specific cities, regions (such as urban or suburban areas), or specific populations (such as individuals with autism).
2. Papers that focus on very specific sub-problems such as the orienteering problem or data augmentation in the tourism domain.
3. Papers that propose only a theoretical framework without utilizing any dataset for experimentation.

Paper Mapping. To identify relevant studies for our review on POI recommendations, we conducted a systematic paper mapping process depicted in Figure 3. The process involved multiple steps to screen, filter, and extract key information from the retrieved papers (Page et al, 2021).

First, we formulated a comprehensive search query using relevant keywords related to POI recommendations (see above). This query was applied to the DBLP database with an additional filter based on the year of publication, type of paper, and journal ranking, resulting in an initial pool of 217 papers.

Next, we conducted a preliminary screening based on the titles and abstracts of these papers. We carefully reviewed each paper to assess its relevance to our research topic, resulting in the exclusion of papers that did not align with our focus. After this initial screening, 160 papers remained. Finally, a further refinement was done by excluding papers that did not specifically address POI recommendations, resulting in a final set of 117 eligible papers. We thoroughly read and analyzed these papers to extract and summarize the key information pertinent to our research objectives.

Overall, the paper mapping process ensured a rigorous and systematic approach in selecting relevant studies for our review. The chosen papers provide valuable insights into the current state-of-the-art of POI recommendation research, which will be presented in detail in the subsequent sections of this review.

²We recall that in next-POI recommendation settings, the sequence of the previous POI visit events matters, see also Figure 2.

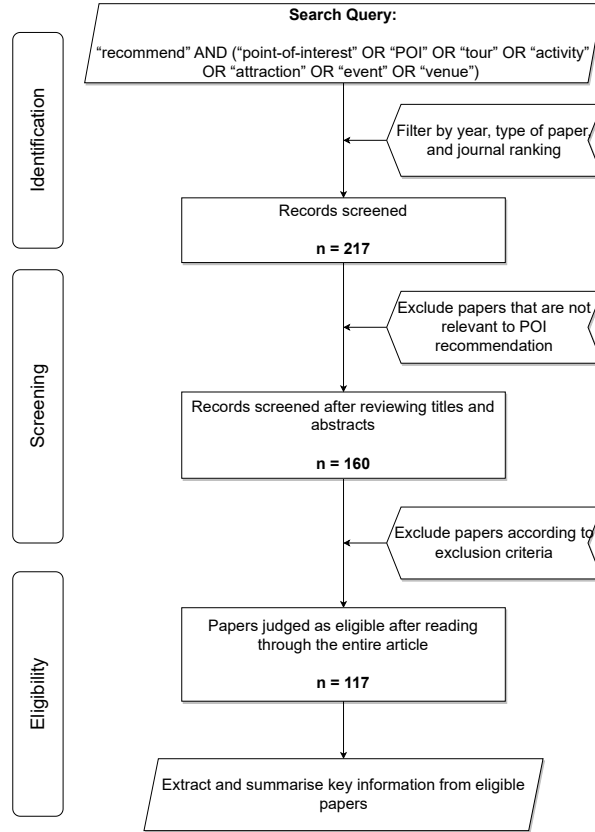


Fig. 3: Mapping Process for Identifying Relevant Papers on POI Recommendations

4 A Landscape of POI Recommendation Research

This section provides an overview of the state-of-the-art research in in-trip POI recommendations from the perspectives of techniques, data and evaluations. Specifically, we will first present the results of a statistical analysis of research papers published in journals from 2017 to 2022, highlighting the trends and patterns in how researchers have approached technical advancements, data collection and evaluation metrics. Building on these findings, we will then delve deeper into how the use of heterogeneous data sources has been applied in the field of POI recommendations.

4.1 Trends and Developments in POI Recommendations

Based on the methodology described in Section 3, a total of 117 original research papers and review articles published between 2017 and 2022 were collected, with their annual distribution depicted in Figure 4. The results indicate a consistent increase in the number of original research papers published in each successive year. Notably, there was a significant surge in the number of papers published in 2021 and 2022.

These findings not only demonstrate a growing interest in in-trip POI recommendation research, but also highlight the necessity for continued exploration and evaluation of this field.

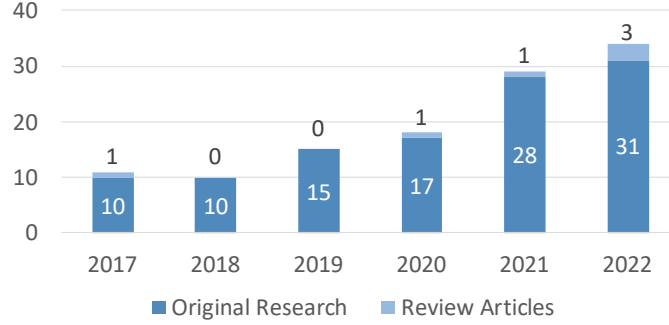


Fig. 4: Annual Distribution of Collected Papers on POI Recommendations

In the literature, we can generally distinguish between approaches that generate POI recommendations based on a given *set* of previously visited POIs by a user, and approaches that target at the *next-POI* recommendation problem by also taking the *sequence* of previously visited POIs into account. The next-POI recommendation therefore represents a specific form of sequence-aware recommendation problems (Quadrana et al, 2018), which have attracted significant research interest in recent years.

The proportion of research dedicated to the general (sequence-agnostic) POI recommendation and the next-POI recommendation is depicted in Figure 5a. While research on the general POI recommendation continues to be predominant, the proportion of original research that has concentrated on the next-POI recommendation has been gradually increasing over the years, as evidenced by the distribution of the two application domains presented in Figure 5b. These trends suggest that there is a growing interest in exploring the potential of the next-POI recommendation, which may lead to further advancements in this field.

4.2 Techniques and Approaches in POI Recommendations

Through the analysis of the collected research papers, it becomes evident that all three main families of recommendation approaches (collaborative filtering, content-based filtering, hybrid techniques) are used to build POI RSs. Among these techniques, CF stands out as the most extensively utilized approach, demonstrating its prominence in the field. Traditionally, CF methods are categorized as either being memory-based or model-based, where nearest-neighbor methods are the most commonly used memory-based approaches, and where model-based approaches include all sorts of supervised machine learning techniques (Jannach et al, 2010; Nikolakopoulos et al, 2021).

Notably, the advent of neural networks has sparked considerable interest among researchers in recent years. Neural network architectures have been leveraged to train



Fig. 5: Evolution of Application Focus in POI Recommendation Research

prediction models using the user-item matrix, facilitating the generation of personalized recommendations. As a result, the adoption of model-based collaborative filtering has witnessed a significant surge, with nearly half of the studies incorporating such techniques. The results of our analysis regarding the underlying technical approaches are shown in Figure 6.

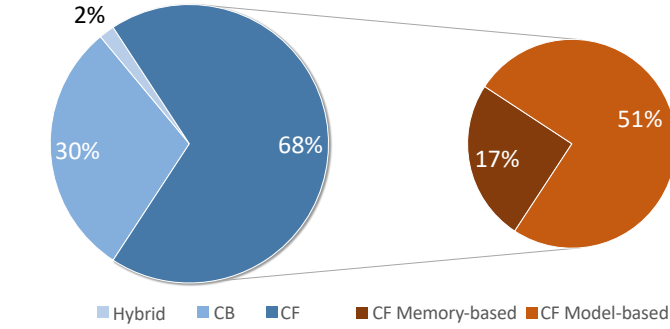
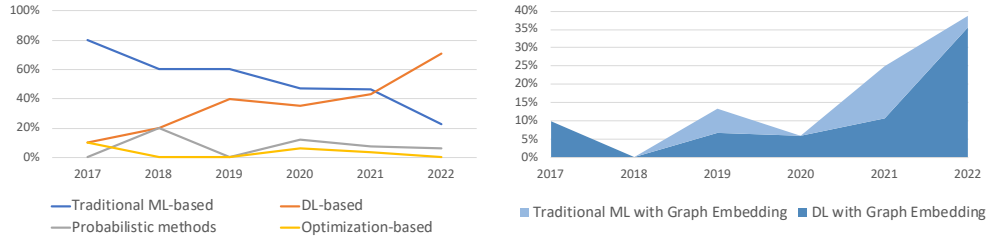


Fig. 6: Techniques Employed in POI Recommender Systems

Upon a more granular examination of the methodologies employed in the collected POI recommendation studies, we categorized these into research implementing traditional machine learning (ML) techniques, deep learning (DL) techniques, probabilistic methods and optimization techniques. To illustrate the evolution in the proportion of papers employing these distinct methodologies over time, Figure 7a presents the temporal trend in research based on aforementioned methodologies. In the initial years encompassed by our study, traditional ML techniques, matrix factorization (Cui et al, 2017; Baral and Li, 2018; Cai et al, 2018) and Bayesian Personalized Ranking (He et al, 2018; Li et al, 2019) were predominantly utilized for POI RSs. However, in recent years we have observed a notable surge in the use of DL techniques, which excel at pattern extraction and accurate predictions for POI recommendations, e.g., with the help of recurrent neural networks (RNN) (Chen et al, 2022; Hossain et al, 2022) or

convolutional neural networks (CNN) (Sang et al, 2021). This upswing is indicative of the growing acknowledgment of the efficacy and flexibility of deep learning algorithms in dealing with intricate recommendation tasks. Furthermore, there were also some studies based on probabilistic methods such as kernel density estimation (Zhou et al, 2022; Huang et al, 2021a), and optimization-based methods such as greedy algorithms (Werneck et al, 2021a; Han and Yamana, 2019), but these were always in the minority.

As shown in Figure 7b, another remarkable trend observable since 2021 is the rising adoption of graph-embedded approaches in both DL- and traditional ML-based studies within the domain of POI RSs. By leveraging graph structures, these methodologies aim to capture complex relationships and associations among tourists and POIs, thereby facilitating more comprehensive and context-aware recommendations (Dai et al, 2022; Hu et al, 2021; Christoforidis et al, 2021). This mounting interest in graph-embedded techniques signifies the increasing appreciation for exploiting inherent data structures and dynamics for crafting effective recommendations.



(a) Annual Distribution of Different Methodologies (b) Graph Embedding Adoption in DL- and Traditional ML-based Methods

Fig. 7: Trends in Utilization of Recommendation Methods in POI RSs

In the context of applying modern deep learning techniques to recommendation problems, it was observed that the excitement for deep learning may have led to some rushed evaluations and a partially limited level of reproducibility, which may have hampered the achievement of true progress to a certain extent (Ferrari Dacrema et al, 2021). To see if similar problems may appear in POI recommendations, we were paying particular attention to reproducibility aspects when reviewing the technical approaches.

The availability of source code in the surveyed studies is depicted in Figure 8. A notable observation is that a significant number of papers solely provided pseudocode, which presents a high-level representation of the algorithms or methodologies without offering the actual implementation details; a larger portion of the papers did not include either the source code or pseudocode, thus restricting the ability to replicate and validate the research findings. Conversely, only a small proportion of the papers (10%) provided the source code, which contributes to the reproducibility and transparency of the research process. The distribution of code availability in the domain of POI recommendation research reflects the varying levels of reproducibility. This underscores the significance of promoting the sharing of source code to enhance the

credibility and reproducibility of research outcomes. The provision of source code empowers other researchers to replicate, verify, and extend existing work, fostering an environment of openness and facilitating scientific progress in the field.

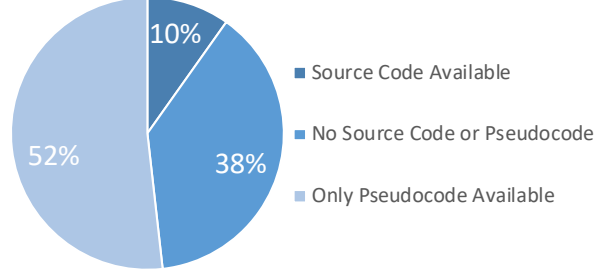


Fig. 8: Availability of Code in POI Recommendation Research Papers

4.3 Data Utilization in POI Recommendations

In our next analysis, we direct our attention towards the status of today’s research in terms of data collection and usage in the context of POI recommendations, as the use of appropriate datasets plays a crucial role in the development and evaluation of POI RSs. A high-quality dataset can provide valuable insights into user preferences, behavior, and context, which are essential for designing effective recommendation algorithms. Figure 9 provides an overview of the different ways data is collected for POI recommendation research. We can observe that a majority of studies relies on published open data, which is a readily available and easily accessible source of information. A smaller proportion of studies employed self-collected data either extracted from websites through crawlers or APIs or gathered by surveys. A few papers finally do not specify how they collected the data used in their studies. Overall, the analysis shows that open data is the most frequently used source of data in POI recommendation research, likely due to its convenience and abundance.

Compared to studies that rely on self-collected data, which are often limited in terms of publicly available information, the utilization of published open data in papers presents a more transparent and accessible source of data. Table 2 provides a concise overview of published open data utilized in the surveyed papers, while Figure 10 illustrates their utilization proportions in POI recommendation research. The findings show that more than half of the studies that utilize open public datasets make use of data from the Foursquare and Gowalla platforms. In contrast, the utilization of data from other platforms in the context of in-trip POI recommendations appears to be relatively limited. The data sources included in Figure 10 represent platforms that were utilized by at least two papers, thereby excluding platforms that were not extensively employed in the surveyed research. It is worth noting that these platforms

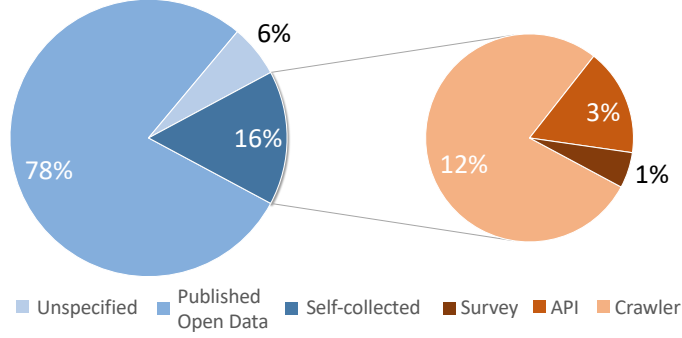


Fig. 9: Overview of Data Collection Approaches in POI Recommendation Research

offer multiple versions of these datasets, varying in terms of time span, geographical coverage, and other relevant characteristics.

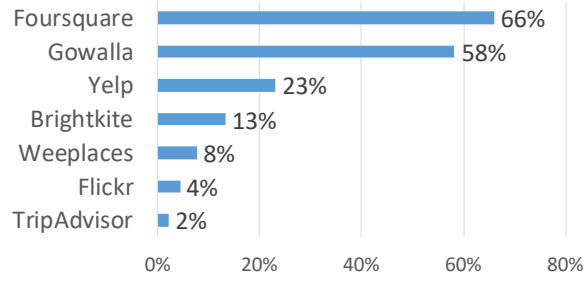


Fig. 10: Utilization Proportions of Open Datasets in POI Recommendation Research

To investigate the varied data types employed as inputs in RSs, this study extends the taxonomy by [Wu et al \(2023\)](#). The taxonomy is expanded to classify pertinent data sources during the in-trip phase into four principal categories: tourist, POI, interaction, and context. By analyzing the collected papers, this study categorizes the utilized data types into these four categories and provides a summary of their respective attributes. The schematic representation of this classification is presented in Figure 11. Additionally, the relative proportions of the major data types used in POI recommendation research are presented in Figure 12.

Upon analyzing the utilization of data types in POI recommendation research, a noteworthy tendency towards a limited amount of data types is presented. Over 50 % of the surveyed papers leverage check-in data, incorporating both timestamp and geographic information, as a primary data source for their research on in-trip POI recommendations. Social relationship information, including friendship networks and social connections, is the second most commonly utilized data type, particularly in recent years where graph-based approaches have gained prominence ([Cai et al, 2022](#);

Table 2: Overview of Published Open Data Utilized in POI Recommendation Research

Platform	Description
<i>Foursquare</i>	
Global-scale Check-in Dataset	33,278,683 global-scale check-ins by 266,909 users, covering 3,680,126 venues across 415 cities in 77 countries from April 2012 to September 2013; (Yang et al, 2016, 2015a)
NYC and Tokyo Check-in Dataset	227,428 check-ins in New York City and 573,703 check-ins in Tokyo, spanning from 12 April 2012 to 16 February 2013; (Yang et al, 2015b)
Weeplaces Dataset	7,658,368 check-ins generated by 15,799 users over 971,309 locations
<i>Gowalla</i>	
Stanford Large Network Dataset	6,442,890 check-ins and an undirected friendship network with 196,591 nodes and 950,327 edges between February 2009 and October 2010 (Cho et al, 2011)
<i>Yelp</i>	
Yelp Open Dataset	908,915 tips provided by 1,987,897 users and aggregated check-in information over time for each of the 131,930 businesses
<i>Brightkite</i>	
Stanford Large Network Dataset	4,491,143 check-ins and an undirected friendship network with 58,228 nodes and 214,078 edges between April 2008 and October 2010 (Cho et al, 2011)
<i>Flickr</i>	
YFCC100M	99.2 million photos and 0.8 million videos, spanning from 2004 until early 2014 (Thomee et al, 2016)
Flickr User-POI Visits Dataset	A set of users and their visits to various POIs in 8 cities, which are determined based on YFCC100M Flickr photos Lim et al (2015, 2016)
<i>TripAdvisor</i>	
TripAdvisor Dataset	Ratings for POIs in the South Tyrol region of Italy that are tagged with contextual situations described by the conjunction of contextual conditions coming from type, month and year of the trip (Braunhofer and Ricci, 2016)

Zhang et al, 2021; Christoforidis et al, 2021). POI profiles (e.g., category and characteristics of POIs), user feedback (e.g., ratings and reviews) and other information (e.g., POI visual content, weather context, POI popularity and tourists’ demographic information) constitute smaller proportions of the utilized data types.

All mentioned information types possess the potential to effectively capture tourists’ preferences for POI recommendations. Collectively, these information types can be classified into two categories: implicitly or explicitly provided information.

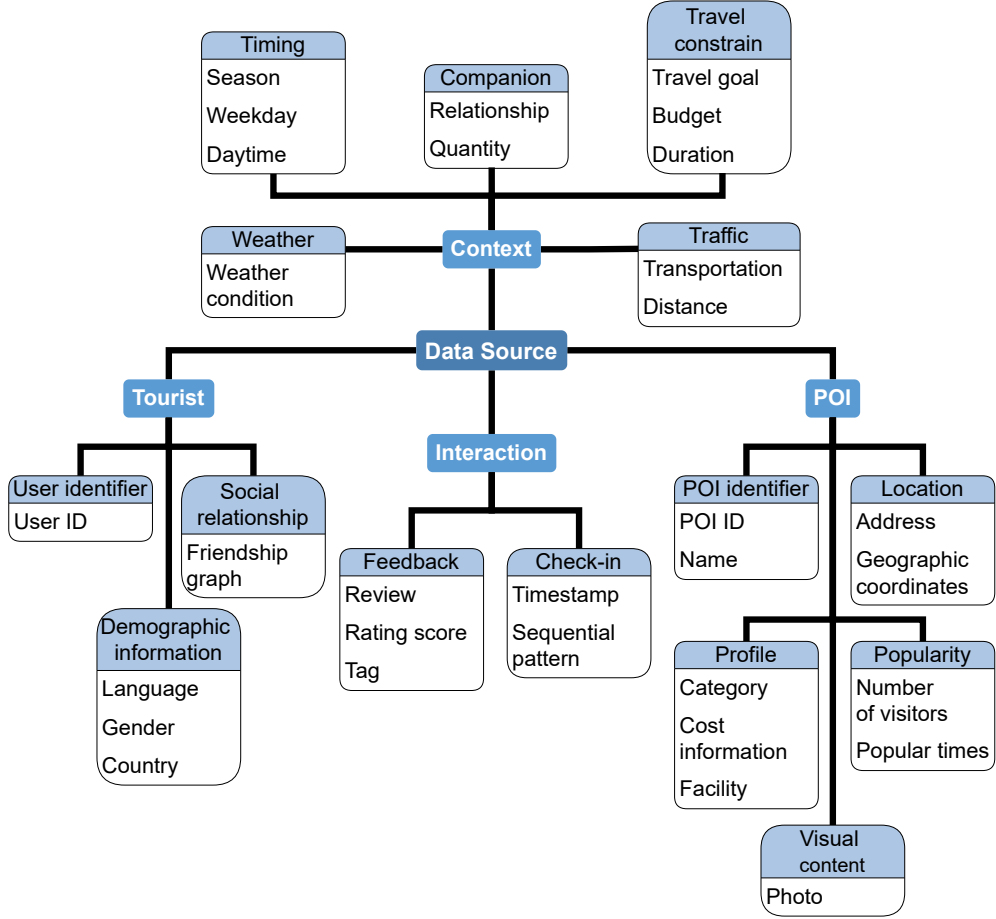


Fig. 11: Taxonomy of Data Sources for POI Recommendations

Explicitly provided information refers to the data that directly reveals tourists' preferences, such as ratings, reviews, and feedback comments. This type of data provides a deliberate, unambiguous, and intentional quality assessment of user preferences, enabling the generation of recommendations that align with those preferences (Kordumova et al, 2010). Implicitly provided information is typically inferred from user behavior and interaction patterns, such as clickstream data, search queries, and consumption histories, which can provide valuable insights into tourists' preferences and interests as well (Jannach et al, 2018).

Explicitly and implicitly provided information offer distinct levels of expressivity regarding the user's preferences, and a combination of the two can lead to more accurate and effective recommendations (Jawaheer et al, 2010). However, in the surveyed papers, as shown in Figure 13a, the majority of studies solely relied on a single type of information, either implicitly or explicitly provided. Only a small percentage of the

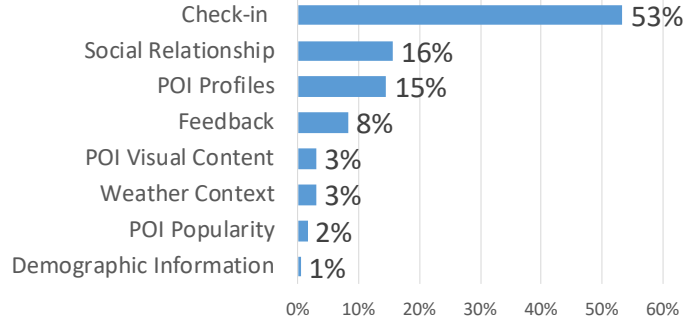
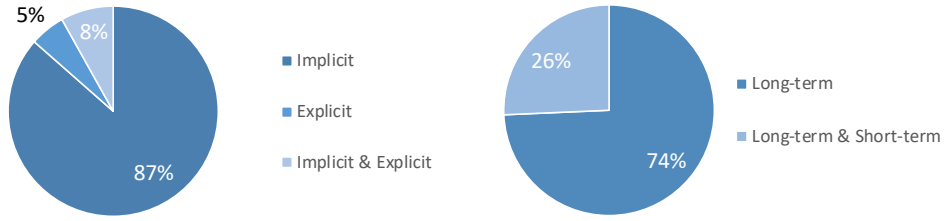


Fig. 12: Information Type Utilization for In-Trip POI Recommendations

papers simultaneously utilized both types of information, such as incorporating check-in data along with reviews or ratings (Liao et al, 2021; Abbasi-Moud et al, 2021a; Pang et al, 2020).



(a) Explicit and Implicit Information

(b) Long-term and Short-term Preferences

Fig. 13: Analysis of Information Feedback Types and Preferences in POI Recommendation Research

An orthogonal question in the context of information on user preferences lies in their temporal dimension, i.e., we can distinguish between long-term and short-term preferences. Long-term preferences are inherent and relatively stable, such as preferred weather, activities and travel mode, which are influenced by the user’s personal background, such as age, gender, education, and income (Bennett et al, 2012). Short-term preferences convey the user’s tourism intention in a relatively short period and can be affected by transient events, such as impromptu short weekend trips or special personal occasions, like business travel. These preferences change more frequently and strongly compared to long-term preferences (Guo et al, 2019).

Both long-term and short-term preferences play pivotal roles in providing POI RSs with a potential to delivering precise and dynamic tourism recommendations that align with the evolving context. However, after analyzing the collected studies, as depicted in Figure 13b, it is evident that the majority of research primarily relies on

tourists’ historical data representing their long-term preferences for generating POI recommendations. The investigation of short-term preferences has received relatively limited attention. It is only in recent years, with the emergence of sequence-aware and session-based methods, that this situation has begun to change. Long Short-Term Memory (LSTM) based network architectures have for example been explored in the domain of POI recommendations, facilitating the consideration of both long-term and short-term preferences of tourists, such as in [Liu et al \(2022\)](#); [Huang et al \(2021b\)](#); [Wang et al \(2021\)](#).

4.4 Evaluation Metrics and Approaches in POI Recommendations

By leveraging learned preferences of tourists from the aforementioned data, POI RSs strive to provide diverse types of tourism-related recommendations. However, evaluating the quality of these recommendations poses a significant challenge. Evaluation methodologies for RSs can be categorized into offline evaluations, lab/user studies, and online A/B testing ([Jannach, 2023](#)). Offline evaluations involve training models on a training dataset and then evaluating their performance on a test dataset; lab/user studies typically encompass the invitation of a selected group of users to participate in an experiment, with subsequent collection and analysis of their feedback regarding the recommendations; online A/B testing entails randomly assigning users of a fielded system to groups using different recommendation algorithms and then comparing the user behaviors across these groups, such as click-through rates, purchase rates and user satisfaction levels to discern the effectiveness of the respective recommendation algorithms. Offline evaluation, in contrast to the other two evaluation methods, focuses on evaluating the effectiveness of recommendation algorithms using pre-collected historical data. Although this approach assumes that only evaluations present in the test set accurately define user preferences, it offers a quick and cost-effective means of evaluating the performance of a recommendation system ([Ricci et al, 2021](#)). Thus, offline evaluation remains essential for investigating specific aspects of recommendation algorithms ([Jannach et al, 2021](#)).

Analyzing the collected papers, we found that the majority of research in the POI recommendation domain relies on offline evaluation. Offline evaluations enable the assessment of recommendation quality from various perspectives, such as relevance, diversity, novelty, and serendipity ([Alhijawi et al, 2022](#)). Nevertheless, it is important to note that, apart from the few research studies (such as [Han and Yamana \(2019\)](#); [Werneck et al \(2021a\)](#); [Chen et al \(2021\)](#); [Rahmani et al \(2022b\)](#)), most of the research primarily focused on relevance (technically, through prediction accuracy) when evaluating recommendations. The evaluation metrics frequently employed for relevance measures are illustrated in Figure 14. Among these metrics, Recall and Precision measures represent a significant proportion, indicating their prominent role in evaluating recommendation relevance. In addition to recall and precision, other evaluation metrics such as Normalized Discounted Cumulative Gain (NDCG), F1-score, Accuracy, Mean Reciprocal Rank (MRR), Mean Average Precision (MAP), Root Mean Square Error (RMSE), Area Under the Curve (AUC), and Hit Ratio are also employed as complementary measures. These metrics contribute to the comprehensive evaluation

of the relevance of the predicted POI recommendations in comparison to the actual tourists' visit history.

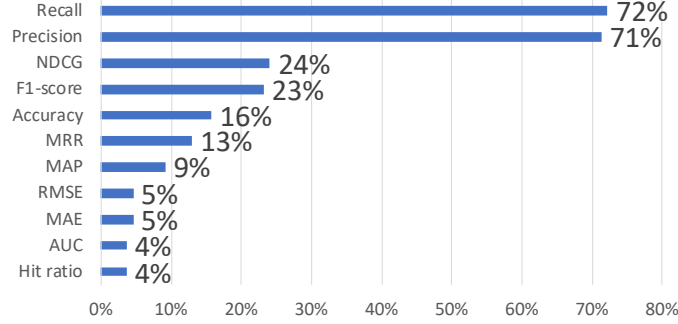


Fig. 14: Evaluation Metrics for Relevance Measures in POI Recommendation Research

During the evaluation process of POI RSs, researchers often compare the performance of their systems against baseline approaches. In our analysis of the collected papers, we observed that a variety of baselines is used, indicating the absence of a universally accepted standard baseline for POI recommendation research. However, we identified several baselines that were chosen by a slightly higher percentage (more than 5 papers), which we summarize and present in Table 3. The findings indicate a prevailing reliance on non-machine learning methods as chosen baselines in the evaluation of POI RSs, highlighting their enduring significance in this research domain. In contrast, the utilization of alternative methods as baselines appears to be comparatively limited.

Contrary to the widespread use of offline evaluations in POI recommendation research, only a few studies have conducted lab/user studies to evaluate their POI RSs. For instance, [Ji et al \(2021\)](#) comprehensively measured model performance from multiple perspectives in an offline setting while also addressing the efficiency of online recommendations across two datasets involving 9,000 users. Similarly, [Massimo and Ricci \(2021\)](#) designed an online user study to gauge user-perceived novelty and appreciation of the recommendations. However, overall, the utilization of lab/user studies in POI recommendation research remains relatively limited. Moreover, the application of online A/B testing was not observed in the papers reviewed for this study.

5 Discussion

In this section, we further elaborate upon the results obtained in Section 4, specifically discussing the application of multiple data types and methods for integrating heterogeneous data in the field of POI recommendations. We shall further identify existing gaps in current research and explore potential future directions and research opportunities.

Table 3: Baseline Approaches for Evaluation of POI Recommender Systems

Baseline	Description
GeoMF	Geographical modeling and weighted matrix factorization (Lian et al, 2014).
Rank-GeoFM	Ranking-based geographical factorization model (Li et al, 2015).
LRT	Location recommendation framework with temporal effects in terms of temporal regularization and temporal aggregation (Gao et al, 2013).
FPMC	Combination of common Markov chain and normal matrix factorization model (Rendle et al, 2010).
FPMC-LR	Personalized Markov chains in the check-in sequence and users’ movement constraint (Cheng et al, 2013).
LORE	Sequential influence on location recommendations (Zhang et al, 2014).
USG	User preference, social influence and geographical influence (Ye et al, 2011).
GeoSoCa	Geographical correlations, social correlations and categorical correlations among users and POIs (Zhang and Chow, 2015).
LSTM	Recurrent network architecture in conjunction with an appropriate gradient-based learning algorithm (Hochreiter and Schmidhuber, 1997).
ST-RNN	Extended RNN that models local temporal and spatial contexts in each layer (Liu et al, 2016).
GE	Sequential effect, geographical influence, temporal cyclic effect and semantic effect by embedding relational graphs into a low dimensional space (Xie et al, 2016).

5.1 Utilization of Multiple Data Types in POI Recommendations

In recent years, the availability of extensive and diverse data sources has provided an opportunity for researchers to enhance the recommendation process by capturing different aspects of user preferences, POI characteristics, and contextual information. However, looking at Figure 15a, we observe that a substantial fraction of research, more than one third of the studied works, only rely on one single type of information in the recommendation process. Most commonly, such approaches are based on past user-item interaction databases. As a result, many approaches in the literature miss the opportunity to reach more accurate recommendations that may be obtained by considering other types of information. Notwithstanding the fact that the majority of studies strive to integrate multiple data types to decipher tourist preferences towards POIs, the diversity of data types employed remains notably limited. We represent the attributes or the attribute combination derived from tourist-POI interactions along the x-axis and attributes from users or POIs characteristics along the y-axis, and utilize a heatmap to illustrate the quantity of collected POI recommendation papers that opted for different combinations of data types. This visualization is provided in Figure 15b.

It is noteworthy that in the field of POI recommendation research, the primary data type combinations revolve around tourist-POI interactions and the social relationships of tourists or POI profiles. For instance, the quantity of papers leveraging

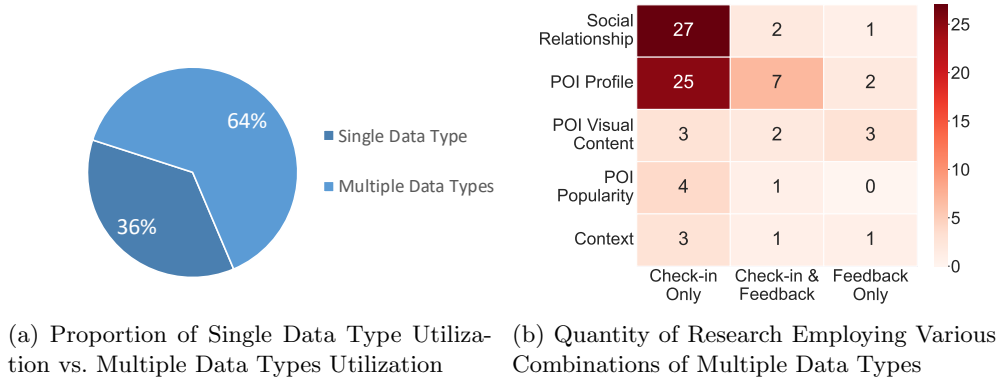


Fig. 15: Heterogeneous Data Utilized in POI Recommendation Research

check-in data in conjunction with a friendship graph (i.e., social relationships) or POI category (i.e., POI profiles) almost approaches half of the collected papers. Besides, the joint utilization of check-in and feedback data offers notable advantages, since feedback data provides explicit insights into user preferences and dislikes. By considering negative samples, the recommendation models can effectively account for user dislikes and improve the overall recommendation quality (Abbasi-Moud et al, 2021b). Additionally, while some papers attempt to incorporate context, they generally focus on considering weather information of the POI’s location (Hossain et al, 2022; Massimo and Ricci, 2021; Abbasi-Moud et al, 2021b; Sun et al, 2019; Trattner et al, 2018), with only a minority of studies striving to integrate other contextual factors, such as time, travel constraints and traffic (Esmaeili et al, 2020; Braunhofer and Ricci, 2017). This tendency might be attributed to the limited types of data provided in public datasets which are predominantly employed by the majority of papers, leading to a lack of information related to tourists, POIs, and contextual factors.

Moreover, even when leveraging existing datasets, current research in POI recommendations does not fully exploit the potential of these resources, and certain types of data remain underutilized. For instance, a mere two of the surveyed papers utilized POI visual information, i.e., image data from the public Flickr dataset.

Cui et al (2017) propose a method to use image data for POI recommendations, which is based on the extraction of user preferences from the implicit feedback encoded in their uploaded geotagged photos. A user-POI matrix is created, with its entries representing the preference score of a user on a POI. This score is calculated by counting the number of photos uploaded by a user that have geotags matching a POI. To construct the POI hypergraph, five types of low-level visual features are used to represent each photo, namely color histogram, color correlogram, edge direction histogram, wavelet texture and blockwise color moment. These features characterize photos from the different perspectives of color, shape, and texture.

Sang et al (2021) propose a deep neural network model called LSVP for POI recommendations on sparse check-in data. The model leverages images to make recommendations, integrating visual content and sequential patterns for more accurate

recommendations, thus addressing the issue of data sparsity. In the LSVP model, the authors chose the VGG16 model as the CNN architecture to extract visual preferences from user-generated photos, and then long-term and short-term preferences are extracted from check-in sequences. Finally, an adaptive attention mechanism is used to balance all extracted user preferences.

Compared to the majority of studies that solely use check-in data for POI recommendations, the introduction of POI visual content significantly enhances the model’s ability to learn tourist preferences, which can help to notably outperform some of the latest models (Sang et al, 2021). This example illustrates that there is considerable room for improvement for POI recommender system performance when utilizing underused data types in current databases.

5.2 Integration of Heterogeneous Data in POI Recommendations

When confronted with varying types of data, the methodologies employed by current POI recommendation research to integrate these heterogeneous data warrant exploration within the context of this survey. From the research papers utilizing multiple data types, it is observed that the methods of integrating heterogeneous data vary according to the distinct recommendation approaches used in the respective studies.

In the realm of CF-based POI recommendation research, factorizing the user-item check-in matrix is a common approach. To utilize data types beyond check-ins, a prevalent method of integration involves constructing a unified objective function to fuse these heterogeneous data, which can manifest as regularization terms within the objective function to represent the influence of these factors. For instance, Xu et al (2021) proposed a novel multi-factor-based POI recommendation method that integrates tourist social relationships, tourist preferences, check-in time and geographical locations into a matrix factorization-based recommendation method. A distinct advantage of this approach is that it not only facilitates the integration of diverse data types but also retains interpretability to a certain extent.

With the increasing adoption of DL-based methods in the field of POI recommendations, an increasing number of studies are leveraging advanced techniques to effectively integrate information from diverse data sources, capturing the intricate relationships and patterns inherent in the data. For instance, Huang et al (2020) integrated different types of data using a dual-attention network (DAN-SNR) that captures both social and non-social influences in POI recommendations. The authors firstly transformed five types of information—user information (including social relationships), POI information, spatial information, temporal information and location information—into embedding vectors to obtain latent representations for each user. Subsequently, these embeddings are concatenated to derive a hidden representation for each check-in. Upon obtaining the hidden representation for each check-in, the authors employed a self-attention mechanism to simulate interactions between user check-ins, capturing social, sequential, temporal and spatial influences regardless of the type of the involved check-in information. Moreover, the self-attention mechanism can automatically measure behavioral relevance between check-ins and adjust attention weights accordingly to predict the next POI. The combination of these methods

allows deep learning approaches to effectively process and integrate different types of data, thereby enhancing the accuracy and efficiency of POI recommendations.

Moreover, as depicted in Figure 7b, graph-based methodologies have been garnering increasing interest within the realm of POI recommendation research. The integration of heterogeneous information through graph structures facilitates the exploration of intricate interdependencies between users, POIs, and contextual factors. Noteworthy studies in this domain, such as the one conducted by Zhang et al (2021), employed Graph Neural Networks (GNNs) to learn representations of users and POIs. GNNs are particularly adept at handling complex graph data by learning high-quality node representations. In this study, a Location-Based Social Network (LBSN) graph was constructed, wherein each user is interconnected with other users via social relations and with POIs via check-in activities. Subsequently, a latent representation of the target user nodes is generated by merging the outputs of social neighbor integration and POI neighbor integration via a neural network. A significant advantage of this model is its ability to automatically learn the weights of neighbors from the data, thereby modeling complex and multifaceted social relationships. This example underscores the potential of graph-based methodologies to enhance the accuracy and effectiveness of POI recommendations by incorporating and harnessing the rich information encapsulated within heterogeneous data sources.

5.3 Open Gaps and Directions for Future Advancements in POI Recommendations

We identified the following research gaps within the current body of work and subsequently propose potential future trajectories and research opportunities to drive advancements in the domain of POI recommendations.

Lack of exploration of diverse attributes from existing datasets. Based on the findings presented in Subsection 4.3, it is evident that the majority of collected papers in the field of POI recommendations primarily rely on a limited set of attributes, predominantly derived from check-in data. While these attributes proved valuable in the recommendation process, there remains a lack of exploration concerning other important dimensions of data.

Addressing the observed lack of diverse attribute exploration in current studies, future research could seek to incorporate underutilized attributes, such as demographic user information and comprehensive POI profiles (including cost and facilities information). Additionally, the integration of a wider range of contextual information, such as time, location and traffic, can lead to more relevant and tailored recommendations, enhancing the overall user experience.

Insufficient exploration of heterogeneous data. Although the utilization of multiple data types to understand tourist preferences has become more and more prevalent in current research, due to the constraints posed by today’s datasets, there remains a lack of a more comprehensive exploration towards integrating heterogeneous data sources. Therefore, a more comprehensive exploration and integration of heterogeneous data sources could lead to significantly improved POI recommendations. Future research could involve developing models that simultaneously consider

the diverse dimensions of tourists, POIs, the interaction between tourists and POIs and context, hence enhancing the accuracy and effectiveness of recommendations.

Limited investigation of short-term preferences. Although Figure 13b illustrates that some research efforts have started to focus on capturing short-term preferences of tourists, particularly through methods such as LSTM-based approaches, the current level of exploration appears limited. Specifically, there is a certain lack of profound research in defining the temporal aspects of short-term preferences in the context of POI recommendations. Time-based considerations and understanding of short-term preferences have not been extensively investigated within the field, indicating a research gap that requires further attention.

The exploration of temporal aspects of short-term preferences could be enhanced in future studies to capture tourists' dynamic needs and interests better. More profound research about robust methods, such as attention mechanisms, are needed to effectively define and understand short-term preferences within the context of POI recommendations.

Underutilization of diverse evaluation metrics. In current POI recommendation research, there exists an overreliance on relevance measures in offline evaluation, such as recall and precision and exhibits an underutilization of diverse evaluation metrics, as emphasized in Subsection 4.4. For example, a general POI recommender system might recommend a first-time visitor to Paris to visit the Eiffel Tower, although the user most likely already knows about this popular attraction. Similarly, when making a next-POI recommendation, it might be predicted that the tourist will visit a nearby cafe based on their current location. While these recommendations might yield high accuracy in offline evaluations, the value of such recommendations to the user can be arguably low. Therefore, while the relevance is of paramount importance, it is equally imperative to recognize the multidimensional nature of POI recommendations, along with the varying preferences and requirements of users. Moreover, the current use of comparably simple models that neglect unique tourist characteristics can engender misleading outcomes and spawn recommendations of limited utility.

Hence, there is a pressing need for future research to diversify evaluation metrics, such as novelty, diversity, serendipity and coverage, to capture the true value and usefulness of recommendations in the specific context of tourism.

Limited reproducibility and transparency. The current landscape of POI recommendation research underscores a crucial need for enhancing reproducibility and transparency, as can be observed from Figure 8. Since open access to source code allows for the verification and extension of existing methodologies, fostering an environment of open science that is conducive to continual innovation and progress in POI recommendation research. The limited availability of source code in a significant number of papers impedes the replication and validation of research findings, potentially hindering the realization of true advancements in the field.

Ensuring reproducibility not only strengthens the validity and credibility of research but also encourages collaboration and knowledge sharing among researchers. Therefore, it is critical for future research to place a stronger emphasis on ensuring

the availability of source code, complete with relevant documentation, to facilitate the reproducibility of studies.

6 Summary

In this work, we have conducted a comprehensive analysis of the current state of research on in-trip POI recommendations. By addressing the research questions outlined at the beginning of the study, we have initially gained insights into the techniques, data utilization and evaluation metrics prevalent in this field. This has facilitated a thorough understanding of the latest research trends in this domain over the past five years. Subsequently, we have focused our attention on the utilization of heterogeneous data within the realm of POI recommendations, discussing exemplars pertaining to the diversity of data types and methods for integrating heterogeneous data. Finally, based on the results derived from this survey, we have identified existing open gaps and proposed potential future research directions.

As the first data-centric survey on POI recommendation research, this study serves as a valuable reference for researchers. It provides a foundation for the development of increasingly accurate, personalized, and context-aware RSs, thereby more effectively catering to the nuanced needs and preferences of tourists.

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