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Gift recommendation systems: a review

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Abstract

Gift exchange is a common practice in people's lives, with a significant proportion of e-commerce sales in the world attributed to gift purchases. However, gift-giving can be challenging for many individuals, as gift-givers often struggle to accurately predict the recipient's reactions. To address this issue, personalized recommendation systems can be utilized to facilitate gift selection. This paper reviews psychological, marketing, and anthropological research related to gift exchange and proposes a framework for gift recommendation systems based on the introduced metrics. Subsequently, the paper surveys existing gift recommendation systems literature and evaluates their adherence to the proposed framework. The contributions of this paper are two-fold: (1) Giving a clear understanding of gift exchange practices and proposing a framework for gift recommendation systems, and (2) Reviewing gift recommendation systems literature and examining their adherence to the provided framework.

Keywords Personalization · Recommender systems · Electronic commerce · Artificial intelligence

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1 Introduction

Gifting constitutes a great proportion of retail sales. In North America, it accounts for about 3.7% of the total annual expenditure [1]. Another study also emphasizes that in the United States, individuals spend an average of USD 1,851 per year on gifts [2]. Therefore, it can be understood that gift exchange is commonplace in people's lives. Although this is a widespread practice, it can be challenging for many individuals.

While many givers attempt to devote a considerable amount of time and energy to buying gifts, the recipients usually are not content with the exchanged gifts [3], however, they would show appreciation and repay as a socially obliged act [4]. Empirical research suggests that gift-givers assume their gift choices are aligned with the recipient's appreciation, they, however, are not able to predict the recipient's reactions accurately even when recommended items are solicited [3]. Additionally, concentrating on the wrong factors and the inability to apply gained experience—as a complementary role of being a recipient—to choosing a gift plays a highlighted part in mis-anticipating the recipients' appreciation [5].

While many recommendation systems are based on personalization, they can be utilized as an approach to facilitate givers in choosing gifts. Thanks to the emergence of new algorithms, computing power advances, and the growth of available information, there has been a growing literature on recommendation systems in recent years. Movies [6], music [7], e-commerce [8], and social media [9] recommendation systems are such of that examples. In spite of these various advances, recommendation systems are not expansively researched and used in the gift exchange paradigm.

In this review paper, our objective is to comprehensively survey the existing literature on gift recommendation systems by carefully examining relevant papers in the research terrain. Our approach involves utilizing a set of relevant keywords across different search engines enabling us to carefully survey all relevant papers in the realm of gift recommendation systems. As far as we are concerned, this paper represents the first comprehensive research in this realm; therefore, the process of selecting keywords and identifying papers aims to be as exclusive as possible. To evaluate the assumptions and methodologies presented in each paper, we introduce a novel framework and assess papers based on their adherence to it. To attentively devise this framework, we present and discuss essential metrics to gift recommendation systems and introduce the framework upon them. However, in order to offer these metrics, investigating gift-giving practices from various disciplines is indispensable. To enhance the readability of the literature review section, we categorize papers into distinct subgroups. While conventional categorization may seem straightforward, we propose a new categorization method based on the most challenging aspects of gift recommendation systems. In summary, this review paper addresses four main research questions:

RQ1: What are the essential metrics for evaluating gift recommendation systems, and how do they contribute to the effectiveness of the gift recommendations?

How can we compare and contrast different approaches and model assumptions based on these metrics?

RQ2: How can insights from other disciplines, be integrated into the design and evaluation of gift recommendation systems?

RQ3: What are the key assumptions and methodologies presented in the existing literature on gift recommendation systems? How do existing research papers in the field of gift recommendation systems adhere to the proposed framework?

RQ4: What are the most challenging aspects of gift recommendation systems, and how have researchers addressed these challenges in their studies? How can the literature be categorized to gain a deeper understanding of the research terrain?

Through the investigation of these questions, our paper offers valuable and timely contributions to the field of gift recommendation systems. To the best of our knowledge, this study represents the first comprehensive attempt to organize the diverse and scattered research in this area into a single article. Since we believe that an understanding of gift exchange practices in the related studies facilitates its recommendation; We based this paper on reviewing psychological, marketing, and anthropological studies of gift exchange to offer a framework for gift recommendation systems whereby the “recommended gift" features are satisfied. Additionally, we hope to provide a clear overview of gift-exchange literature in order to ease future studies of gift recommendation systems. Moreover, current attempts to approach gift recommendation systems are introduced and reviewed and the adherence of each algorithm to the proposed framework is examined. In summary, two of the most valuable contributions of this paper make can be highlighted as follows:

- Reviewing psychological, marketing, and anthropological research related to gift exchange in order to (1) Give a clear understanding of this practice and (2) Offer a framework;
- Reviewing gift recommendation systems literature and examining their adherence to the provided framework.

2 Background and related work

This section serves to introduce the primary terminologies and concepts associated with recommender systems, electronic commerce, and gift exchange. The aim is to provide a foundational understanding of the key terms and ideas that will be utilized throughout the paper.

2.1 Recommender systems

Due to the swift expansion and variety of offerings in various domains, there has been a rise in the number of items available to individuals. Having the opportunity to choose is crucial, however, the act of choosing has negative aspects that become amplified as the number of choices is increased. This is because subjective results of a decision are often more significant to individuals than objective results. In other words, the well-being of the user declines as the range of choices widens, showing that while choice is an advantage, having more choices is not always superior [10]. However, the issue of information overload can be remedied through the use of recommender systems.

Recommender systems refer to software or techniques designed to propose items to a particular user, with the objective of reducing the user's need to evaluate an overwhelming number of potential items. There are two types of recommender systems: personalized, and non-personalized. Personalized recommender systems in their simplest form, offer a personalized ranked list of items to a user, wherein the ranking of each item is proportionate to the user's interest or preference for the item [11]. Non-personalized recommender systems, on the other hand, provide the same suggestions to all users without taking into account individual preferences or behavior. This paper specifically examines personalized recommender systems.

In order to construct a recommender system, a set of data that serves as the source of knowledge should be acquired. In any case, the datasets used by recommender systems may consist of one or more of three types of sources: items, users, and transactions of the user and the recommender system [11]. Additionally, different systems may utilize various approaches to suggest items, such as recommending items that share common attributes with those previously preferred by the target user, or suggesting items that a similar user to the target user has enjoyed [12].

2.1.1 Collaborative filtering method

The collaborative filtering method (CF) is one of the most successful approaches in recommender systems in which recorded preferences of a group of users is used to make a recommendation for a target user [13]. This model assumes that if two users have similar behaviors of usage (e.g., in buying, listening), or rating, they proceed with the same affinity [13, 14]. Therefore, the recommendation process is not supported by extra information of either users or items [14]. In a simple form, in order to observe a target user's preference for an item, similar profiles—neighbors—recorded preferences for that item are combined [15]. Collaborative filtering can be categorized into Memory-Based Collaborative Filtering and Model-Based Collaborative Filtering, with Memory-Based Collaborative Filtering divided into User-Based Collaborative Filtering and Item-Based Collaborative Filtering [16].

2.1.2 Content-based filtering method

In a content-based filtering method (CBF), on the other hand, the recommendation is based upon the target user's interests and items' description by identifying items that are of specific significance to the target user [17]. This model is considered the most elementary among recommendation systems and was commonly utilized in earlier stages of recommendation system developments [16]. Within content-based filtering, each user is expected to function individually and involves training a classification or a regression model through the acquisition of pre-classified data [18, 19]. The database consists of user information which is obtained directly from users or indirectly by observations; and item information which is acquired through the web usually by online parsing [20]. However, while this method is heavily reliant on the previous activities of the user, it is limited in recommending new and various items [16].

2.1.3 Hybrid method

Although both of the aforementioned methods are widely used in recommendation systems, they each have their own limitations. while a collaborative filtering method only relies on users' rating data, a content-based method only considers metadata of items [16]. However, there are other types of recommendation techniques such as demographical recommendation, which recommend based on demographical features derived from personal information; utility-based recommendation, which suggests an item to a user based on a utility function that aims to match the user's current needs and available options; and knowledge-based (KB) recommendation, which makes suggestion leveraged by prior knowledge such as degree of satisfaction of each item for a user need [21].

On the other hand, a hybrid recommendation system integrates two or more recommendation techniques to exploit their advantages and reduce their limitations [22]. There are different strategies for combining two or more recommendation techniques. In the weighted strategy, multiple recommendation techniques are integrated and their outputs are aggregated using a weighted linear function. In the switching strategy, the system changes its recommendation technique depending on the situation. The cascaded strategy utilizes a hierarchy of recommendation techniques in which the previous one refines the suggestions passed to the next one. Mixed recommendation, which is the simplest hybrid strategy, presents the suggestions of several different recommendation techniques simultaneously. In the feature combination strategy, one or more recommendation techniques are utilized as feature extractors, then, these features along with the original features are fed to other recommender(s). The feature-augmentation strategy, which is order-sensitive, involves using the output of one recommendation system—items' score—as an input feature to the next system. Finally, the meta-level strategy uses the produced model learned by a technique as the input to the next technique; in other words, since the user's interest is expressed in the model as metadata, the next technique uses the previously generated representation model which is usually a collaborative recommender [16, 21, 22]. The majority of the literature employs one of the hybrid methods discussed in this subsection.

An overview of recommendation systems that highlights fundamental concepts of content-based filtering, collaborative filtering, hybrid filtering, knowledge-based, utility-based, and demographical recommendation systems is presented in Fig. 1.

2.2 Electronic commerce recommender systems

E-commerce refers to buying or selling services or goods through any electronic means, such as the Internet. There are three different types of e-commerce: B2C

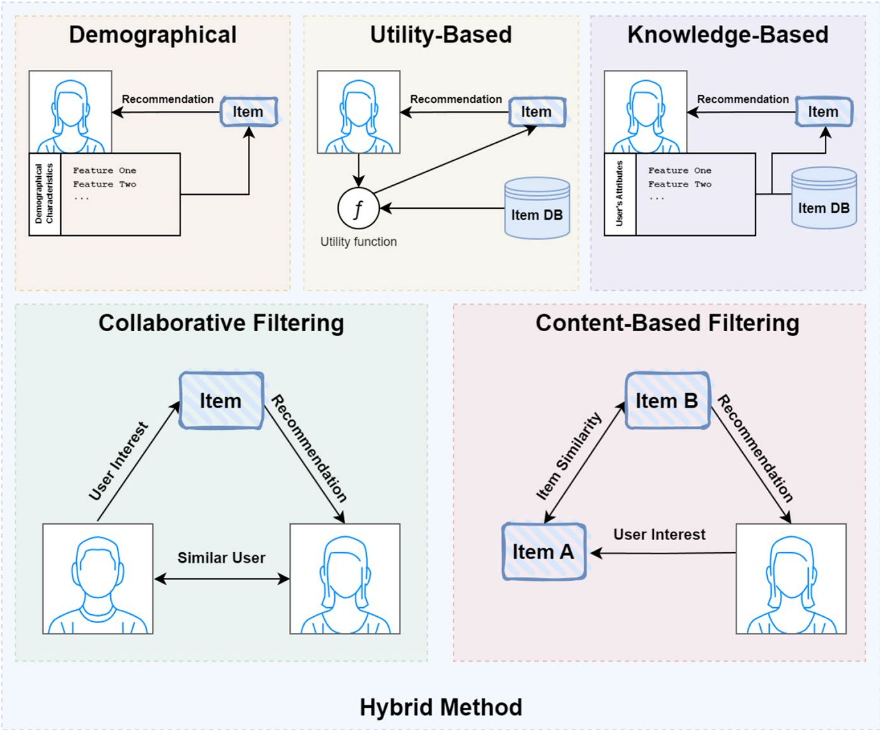

Fig. 1 Overview of different recommendation system approaches. This figure summarizes recommendation systems commonly used in the field: Content-Based Filtering, Collaborative Filtering, Hybrid Filtering, Knowledge-Based, Utility-Based, and Demographical

(business to customer), C2B (customer to business), and B2B (business to business). In this paper, however, we focus on B2C since gift recommendation systems fall within this segment.

With the rise of online shopping and the convenience it offers to customers, e-commerce has increasingly gained popularity; it accounts for 20% of global retail sales in 2023 after around a 12.5% increase from 2015 [23].

Recommender systems in e-commerce ought to boost sales by targeting each customer differently by enhancing the level of personalization for each individual. These systems utilize product data as well as customer data to help individuals exclude the time-consuming task of finding the products that they need by providing suggestions on products integrated with information that helps them with their decision on purchases [24]. In a nutshell, recommender systems contribute to boosting e-commerce sales through three distinct means: (1) Converting browsers into buyers, (2) increasing cross-sell, and (3) Building loyalty [25].

Many different e-commerce recommendation systems have been presented. The review paper proposed by [26] divides e-commerce recommendation systems into seven categories: Collaborative, content-based, demographic-based, knowledge-based, community-based, hybrid, and other methods. On the other hand, another review paper on e-commerce recommendation systems divides methods into the first five aforementioned categories and introduces eight measures for comparison of different methods: Accuracy, diversity/novelty/serendipity, independence, operation cost, response time, scalability, security, and type of data sources [27].

Although both gift recommendation systems and e-commerce recommendation systems use algorithms to suggest products to customers, they are different in their ultimate goals. While in e-commerce, recommendation systems are utilized to boost sales and enhance customer experience by personalizing, in the context of gift exchange, these systems are employed to assist individuals in selecting gifts for others by considering the recipient's characteristics, interests, the occasion for which the gift is intended, giver-recipient's relation, etc.

2.3 Gift exchange

Addressing terminology and notions related to the context of gift exchange can provide a more profound understanding of the setting and be beneficial in comprehending why certain gifts are appreciated while others may be considered a faux pas. This understanding can be valuable in defining metrics in the following section.

Almost any resource, whether tangible or not, can potentially be considered a gift. This inclusive notion of a gift considers objects, services, and even experiences as gifts. However, gifts are context-bounded and can be situationally specific [28]. An appropriate gift in one situation might be regarded as ill-suited in other settings [29]. To put it in other words, a gift might not be able to convey the gift givers intention if the context is not regarded. Yet, some items might exclusively be considered gifts. This designation might be the result of "cultural conventions" or advertising "directed intervention" strategies [28].

Gift exchange is an experience entangled with social, economic, and cultural features [4]. Religious or moral essentials might cause an obligation for individuals to give gifts. According to [30], gift-giving should be selfless, magnanimous, and heartfelt, and the gift itself should be desired by the recipients.

3 Methodology

By conducting a thorough search and evaluation of the literature, we are able to provide a comprehensive and fair review of the current state of research in gift recommendation systems. The methodology used to find papers for this review paper involved three steps.

3.1 Step 1: Keyword search

We chose Google Scholar as the search engine for the keyword search because most of the publications are indexed on this website. Using the combination of relevant keywords including the terms “gift", “recommendation(s)", “recommender(s)", and “personalized", as well as terms related to specific recommendation techniques such as “collaborative filtering", “content-based", “context-aware", “knowledge-based", and “machine learning", a search was conducted utilizing the engine. While, as far as we are concerned, this research is the first of its kind regarding gift recommendation systems, we did not limit the search to a certain time period. We restricted the search of the keywords to titles by using the “allintitle" keyword in the search engine. However, for the keyword "gift recommendation" we did not apply this constraint and searched through all the papers containing the exact keywords anywhere in the article. This search was conducted in February 2023 and Table 1 presents the initial number of search results obtained, the refined results after the screening process, and the results after the evaluation.

In addition to the keyword search conducted on Google Scholar, we also explored the same keywords on other academic databases such as Emerald, Springer, Science Direct, Scopus, and Taylor and Francis in order to ensure the comprehensiveness of the results. However, we found that the search results obtained from these sources are covered by the results obtained through Google Scholar. As a result, to avoid redundancy, we only report the search results obtained from Google Scholar in Table 1.

3.2 Step 2: Screening

After conducting the initial search, the papers were screened based on their relevance to the topic of gift recommendation systems. The inclusion criteria for this review were that the paper should be focused on gift recommendation systems and devise an algorithm or model focused on gift recommendation. Additionally, while the study is limited to English papers, papers in other languages are eliminated.

3.3 Step 3: Journal and Conference evaluation

After identifying the relevant papers, they were evaluated based on the publication venue. The Journal Citation Reports (JCR) index was used to assess the quality of the journals in which the papers were published. In the case of conference publications, a paper was considered authorized if it was presented at an ACM or IEEE

Table 1 Number of papers resulted from keyword searches before and after screening and evaluation

Keyword	Total#	Screening#	Evaluation#
Collaborative filtering gift(s)	2	1	1
Content-based gift(s)	4	1	1
Gift(s) recommendation(s)	27	6	2
Gift(s) recommender(s)	2	1	0
Personalized gift(s)	15	1	1
Gift recommendation	107	6	3
Total Papers	–	16	8

conference or published by Springer or Atlantis. Table 1 presents the results of the search, screening, and evaluation process.

Overall, this methodology allowed us to identify and review relevant papers on gift recommendation systems while guaranteeing that the selected papers are authentic by evaluating their published journal or presented conferences. The total number of relevant papers after screening is 16, and 8 after the evaluation.

The number of papers related to this topic is relatively low; 16 relevant papers were identified through the literature search. The distribution of papers by year is illustrated in Fig. 2. As can be comprehended, most of these papers were published between 2017 and 2019, and the number drops in recent years. While gift recommendation is an important topic, this finding suggests that more research should be conducted in the field.

4 Definition of metrics and gift recommendation framework

In this section, we define metrics for evaluating methods and distinguishing between different approaches. Without metrics, it would be challenging to compare and contrast various recommendation approaches objectively. Metrics allow us to measure the effectiveness of gift recommendation systems, identify their strengths and weaknesses, and ultimately improve their performance. Moreover, based on the introduced metrics and the "recommended gift" attributes, a gift recommendation framework is presented.

However, defining comprehensive metrics for gift recommendation systems can be challenging. This is because gift recommendations involve multiple factors and are subjective to individual users' tastes and preferences. One of the challenging factors to measure is the effectiveness and accuracy of a gift recommendation system,

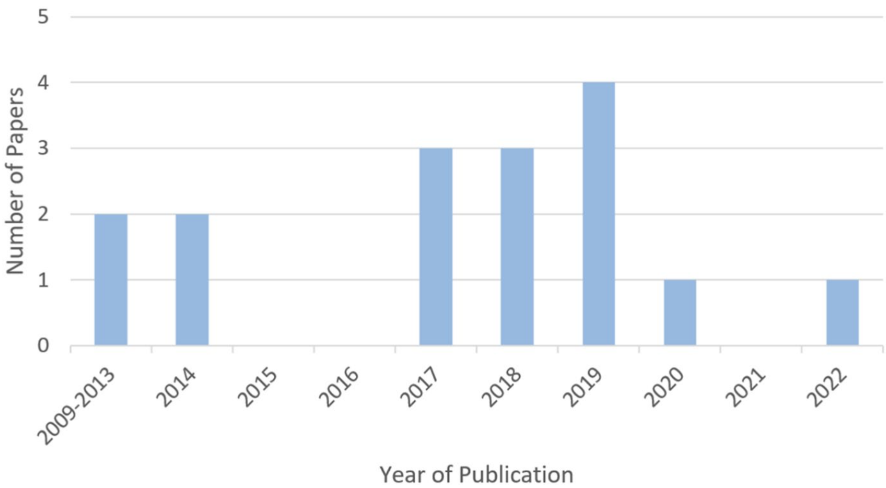

Fig. 2 Distribution of papers in the literature by year. The graph displays the number of papers published in each year from 2009 to 2022

as there is no benchmark dataset. Additionally, gift recommendation systems rely on a wide range of data sources, which can be difficult to compare and integrate into a single metric. Furthermore, privacy and ethical considerations must be taken into account when defining metrics because a personalized recommendation system is based on the user's personal information, and in gift recommendation systems the target user is the intended gift recipient which makes this problem even more challenging. Therefore, defining comprehensive metrics for gift recommendation systems requires careful consideration of these complex factors to ensure that the metrics are accurate and also reflect the performance of different systems in a fair way.

4.1 Accuracy

Accuracy is an essential metric to evaluate the performance of a recommendation system. It measures the degree to which the system can predict relevant items to a user accurately. There are various metrics to evaluate accuracy in a machine learning task. The accuracy of the introduced model is assessed in [31] by asking the gift-givers whether the developed system was helpful in determining a gift for the intended gift recipients. Using a 1-5 rating the model is evaluated based on suitability between the recommended gift with the desired gift. Taking it further, Precision, Recall, and Accuracy are calculated in [32] based on the confusion matrix constructed from users' ratings. Additionally, the same Precision, Recall, and Accuracy measurements are utilized by [33, 34]. However, instead of obtaining it from users' ratings, they assess their presented models based on their own test datasets. While these two models recommend a list containing n gifts instead of a gift to the gift giver, these measurements are defined differently from the previous ones. Basically, it determines whether the correct answer is between the list of recommendations or not. On the other hand, the problem of gift recommendation is considered an optimization task by [35], in which Precision Value (PA) can assess the quality of the recommendation. PA is calculated as below when g is the number of gift categories, n is the number of items, and while *prediction* and *actual_value* are representative of the model tag and true tag of an item.

$$PA = 1 - \frac{\sum_1^n |prediction - actual\_value|}{n(g-1)}$$

Furthermore, two new measurements, Delight and Embarrassment, have been proposed in [36]. Delight inspects whether the selected gifts were the best available in the gift catalog, and Embarrassment measures consider the number of times that the recommended gift is a faux pas.

Despite the similarity in the definition of accuracy, it is trivial to compare methods based on their accuracy. While, as far as we know, there is no benchmark dataset in the literature, each paper train and evaluate its model on a different dataset. Therefore, the accuracy achieved by different methods cannot be set side by side and thus we do not discuss them.

However, we can also consider studies in the psychological, marketing, and anthropological fields. We argue that a gift recommendation system is, to some extent, accurate if it suggests gifts that satisfy some features of a “perfect gift" or the “best gift ever". Utilizing projective techniques, [30] identifies that a “perfect gift" should be desired and appreciated by the gift recipient. The process of choosing a gift must be executed in a careful and thoughtful manner. It also emphasizes unexpected and surprising elements of the gifts. Moreover, a "perfect gift" for some people might fulfill a wish and shows that they are known by the gift giver. An empirical study by [3] suggests that recipients regard requested gifts as more thoughtful and considerate compared to unrequested gifts selected by the gift-givers.

Empirical research by [37] on the “perfect gift" identifies that a perfect gift contains six features: (1) Sacrificing, (2) Altruistic, (3) Luxury, 4) Appreciated, (5) Surprising, and (6) Pleasing. On the other hand, [38] introduces a less utopian gift exchange experience named the "best gift ever". Unforgivable, experimental, and life-changing experiences are the attributes that are often assigned with the concept of the "best gift ever".

As can be seen, there are different attributes regarding the “best gift ever" or a “perfect gift". A “recommended gift" is a gift that focuses on the recipient. It should, at least, fulfill one or more of the attributes pointed out by the aforementioned studies.

4.2 Privacy and data source

Privacy is a concern in the realm of the online world [39]. It is also emphasized in the context of recommendation systems. A personalized recommender has to have access to a portion of a user’s data to discriminate between users. The user information acts as a double-edged sword; the more the recommendation system is aware of such information, the more the user is concerned about her privacy. There are many different personal data such as explicit, implicit, and transactional [25]. While different types of gift recommendation systems need to be granted different levels of personal data, users’ inclination to provide them differs. However, findings of [40] suggest that in a B2C recommendation, users are willing to overlook privacy concerns in exchange for personalization benefits and experience.

The data source is entangled with privacy because it determines to what level a recommendation system needs to access users’ information. Some of the gift recommendation systems rely on transactional sources of information, for instance, they obtain data from an e-commerce website. Some other recommendation systems are based on social network data; therefore, they need to have access to a social network account of the user. On the other hand, some of the gift recommendation systems do not need to be granted access to high-level personal information, instead, they make personalized recommendations based on data obtained from the user explicitly. While different users have different boundaries for their personal information, some of them might prefer a safer platform instead of a more personalized one.

4.3 Scalability

Scalability is also an essential consideration when evaluating gift recommendation methods. A fast and accurate recommendation increases user satisfaction with the provided function. Moreover, operation cost is another concern of online recommendations. If a recommendation technique is operationally costly or inefficient, it might not be effective regarding its economic revenue or it may not be able to be scaled over a large set of data. However, many of the proposed gift recommendation methods do not focus on this attribute, and this might be because many of the methods are not designed functionally for the market. However, many of these methods can potentially adopt scalability attributes at the time of real-world initialization.

Figure 3 introduces the gift recommendation framework in which the presented metrics are considered. The accuracy of the gift recommendation system is proportional to the recommendation method as well as its model's presumption which determines its incorporation of the "recommended gift" attributes. The adherence of the model to "recommended gift" attributes can be evaluated through the model presumptions in the process of recommendation e.g. recommending items regarding the previous purchases of the intended gift recipient. The level of privacy maintained by the model is directly related to its data acquisition method. Some models are dependent on the shared information of the intended gift recipient through an e-commerce website or a social media platform while others might only consider the gift-giver as the source of information. The framework takes into account the scalability aspect of the gift recommendation system as well.

5 Review and analysis of existing gift recommendation systems

In this section, we analyze the selected papers in the literature to explore their gift recommendation techniques and data acquisition methods. Our review covers the techniques employed, as well as their advantages and disadvantages, and their adherence to the proposed framework.

As discussed in Sect. 2, recommendation techniques are traditionally categorized into three distinct methods, namely, collaborative filtering, content-based filtering, and hybrid methods. However, recently proposed recommendation algorithms have been based on the integration of both collaborative filtering and content-based techniques. Furthermore, based on our analysis of the literature, one of the most challenging aspects of gift recommendation is obtaining information about the intended gift recipient. Thus, to emphasize this characteristic, we categorize the selected papers based on their sources for gathering the recipients' information. The selected papers have been divided into three categories: (1) Customer behavior data, (2) Social media, and (3) Manually-entered data. In Fig. 4, a visual representation of the categorized papers and their respective subcategories is provided.

5.1 Costumer behavior data

Methods based on customer behavior data rely on the past behavior and preferences of the intended gift recipient to identify patterns that can be used to provide suggestions to the gift giver. Methods in this category obtain a variety of customer behavior data such as purchase histories, ratings and comments, wish lists, and search patterns, from an e-commerce website. These methods presume that both giver and

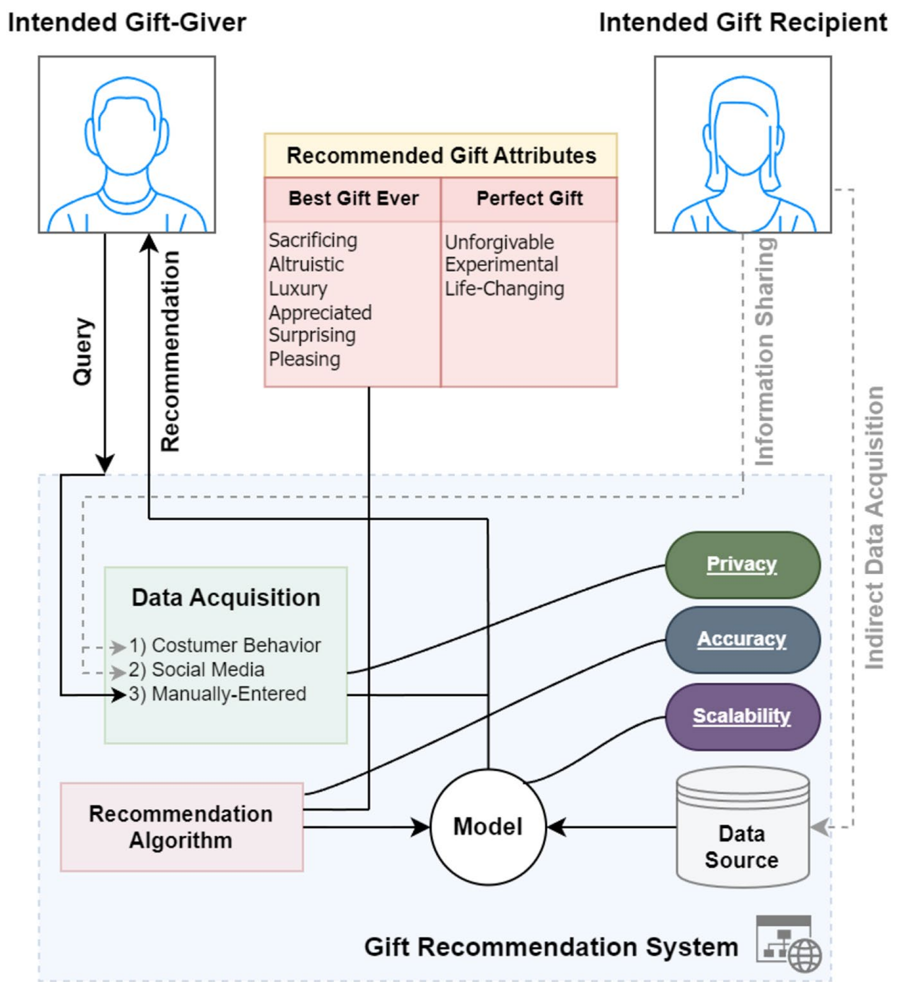

Fig. 3 Gift recommendation framework based on the presented metrics. This figure illustrates the proposed framework for gift recommendation, incorporating privacy, accuracy, and scaling of the system regarding the data acquisition, the recommendation algorithm and its adherence to the recommended gift attributes, and the model, respectively

recipient use the same e-commerce website regularly, thus, the website can be used as a common ground to recommend gifts. The advantage of these methods is that they are provided with a rich source of information that can be utilized to pinpoint the recipient's preferences and interests.

5.1.1 Review of the selected papers with costumer behavior data methods

The introduced mobile gift recommendation algorithm by [41] is based on the previously proposed framework, COREL, which is based on a hybrid approach. Firstly,

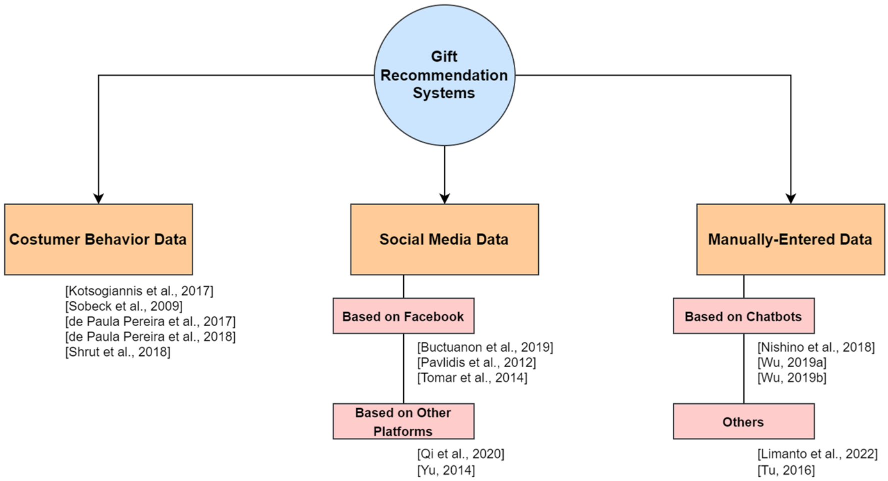

Fig. 4 Categorization of papers in the literature. The figure illustrates the classification of papers into three main categories (Customer Behavior Data, Social Media, Manually-Entered Data) and their corresponding subcategories

the user-item information is collected based on users' evaluation of items in the application. Secondly, a short list of candidate categories and items is produced based on user evaluations. Thirdly, the probability of the interest of the user c_k to the item p_j, meaning $p(c_k|p_j)$, is calculated, which considers refining the list of items based on the prices of the evaluated items. Finally, the list of recommendations is reordered based on the credibility of the item on an e-commerce website. Tunning the parameter p_l defined as the price rate tolerance of the gift giver, the proposed method is evaluated [42]. The accuracy achieved with lower p_l (e.g. 20) is about 55%, while a higher value (e.g. 25) resulted in 76% accuracy.

A hybrid approach for gift recommendation is proposed in [43]. Initially, the similarity between items is calculated based on their attributes. Subsequently, a collaborative-filtering algorithm is executed to score user-item relationships, taking into account the recipient's purchase history, feedback, etc. Based on the approach, suggested gifts are aligned with the recipient's preferences if similar users share similar interests.

On the other hand, [34] views the concept of gift recommendation as a group recommendation that takes into account the preferences of both the giver and the recipient. To address the problem of top-k edge recommendation, they initial a graph $G = (V, E)$ representing individuals and formalize each previous purchase by an ordered tuple (u, i), representing the individual and her purchased item. Therefore, the recommendation for a gift-giver s to a gift-recipient r is a list of items $I_{(r,s)}$ which is sorted based on a relevance function defined on each pair of edge and item. Subsequently, [34] introduces two different approaches to solve this problem: (1) Node-level algorithms, and (2) Edge-level algorithms.

The node-level algorithm requires only the purchase history of each individual. First, it initializes the features of each individual by aggregating features of items in her purchase history. Second, utilizing cosine similarity between individuals, it computes $CF_{N(r)}$ and $CF_{N(s)}$ which address item suggestions based on collaborative filtering for the individuals r and s. Finally, it introduces an allative composition formula in which the features of an item to be gifted to r from s is addressed in a point on the line connecting $CF_{N(r)}$ and $CF_{N(s)}$. Additionally, a cost function is introduced to make the parameter determining the closeness of an item's score to each individual's preferences learnable.

Edge-level algorithm requires personalized information on shared actions between individuals as well. First, it initializes directed-edge-level properties based on the shared actions between individuals. Second, it computes $CFS(u)$ and $CFR(v)$ which address items' features that are given from similar users to u and received from similar recipients to v. Finally, as introduced, a parameter α is used to normalize the additive of $CFS(u)$ and $CFR(v)$. In the end, they introduce a multiplicative formula to address the edge separately based on the features that represent similar givers and recipients.

Compared to more recent papers, [35] is an older study that has proposed four different approaches to gift recommendation. The first two approaches are based on collaborative filtering, while the third approach employs content-based filtering, and the last one is a hybrid combination of the proposed methods. However, compared to [34], these algorithms do not consider the giver's preferences in gift-giving. In the first step of these algorithms, users' profile is actualized with their demographic information and their ratings for a selected list of items.

The first proposed algorithm is based on a weighted modification of the Slope One algorithm introduced by [44], which is based on the popularity differential between items for each individual. The second approach is based on the artificial immune system, which selects a group of users with similar preferences to the intended recipient using weighted kappa. Then, an item rating is calculated based on the closeness of the user based on the introduced weighted kappa. The third approach is a simple cosine similarity-based algorithm that predicts item scores. Based on the graph ant colony optimization, the fourth approach is introduced in which each vertex of the graph represents an item and each ant represents a user. At each step, an ant selects a new vertex to exploit based on a probabilistic rule that incorporates intensity and visibility parameters representing collaborative and content-based components, respectively.

5.1.2 Pros and cons of the costumer behavior data methods

The proposed methods rely on information related to the e-commerce activities of gift recipients. However, it is important to consider that an individual's purchase history might not necessarily reflect her current needs or interests as their needs may have been met. Moreover, the purchase history does not always reflect buyers' preferences because they might be occasions in which the buyer is unsatisfied with her purchase. Additionally, privacy concerns may arise as the platform might require permission to access the recipient's purchase history and item evaluation. These pieces of information—especially when it contains timesteps—can be proportional to the individual's general location. Therefore, having this data collection method permitted by the user in order to have a better gift-receiving experience is far-fetched.

Despite these limitations, customer behavior data remains a valuable source of information for gift-recommending systems. This data can be utilized in order to address some of the underlying aspects of customer-item relations that are not apparent through other means. In addition, by combining this method with other approaches more robust and effective models for personalized gift recommendations would be resulted.

5.2 Social media data

Another approach to obtaining data on the intended gift recipient is to rely on online-available data. Most of these methods rely on social media platforms as their source of information, however, other third-party online sources such as search engines might as well be considered. These methods aim to analyze recipients' interests and behavior by gathering information from their social accounts and creating a personal profile for them. Personal profiles that are built upon social media usually rely on the user's online posts, likes and comments, networks, as well as their friends' online interests. The underlying assumption of this method is that the recipient's social profile is aligned with her preferences and values, therefore, a gift recommendation adheres to her interests. Vast and multi-source online data available is one of the advantages of this method, which can provide reach information about the recipient. Many of the methods introduced by these papers are based on Facebook. In addition, many of the studies in this subsection have been deployed as a website for gift recommendations in the real world.

5.2.1 Review of the selected papers with social media data methods

The gift recommendation system introduced by [32] uses data collected from Facebook accounts such as posts, comments, liked pages, and users' biographies. The paper under discussion combines content-based and collaborative filtering approaches to introduce a hybrid model that is both personalized and effective.

Firstly, users' and items' profiles are constructed based on data collected from Facebook accounts and an e-commerce website, respectively. Examining the harvested data from Facebook, the association degree of each user to one of the seven predefined personalities, namely, music lover, fashion fiend, outdoor enthusiast, sports fan, foodie, and bookworm is calculated. Similarly, through data collected from an e-commerce website, the association degree of an item to each aforementioned category, as well as its association to any predefined event, is calculated.

The paper then introduces a content-based algorithm that takes into account personality, the similarity between the user and the item, and the selected event. Additionally, as part of the collaborative filtering approach, the similarity between users and items is calculated through Pearson correlation, considering personality types as well as age and gender. Using these similarity values, item-based and user-based ratings of each item-user pair are calculated. Finally, the hybrid method combines both approaches by ranking the results of the collaborative filtering methods based on the content-based method. In addition to the data collected from Facebook by [32], the algorithm introduced by [45] also considers the profiles of the intended gift recipient's friends with the aim to infer users' preferences better.

Shopycat, a Walmart application used for gift recommendation based on Facebook data, is introduced in [36]. The application takes into account not only the affinity of the intended gift recipients' interests to gifts but also the "giftability" of the product, price preference, and also, events and occasions. The model builds a Social Genome capturing high-level entities and their relationship based on events, trends, etc. collected from the application activity, Facebook, and Twitter. Then, it infers categories for each activity based on semantic techniques. To find the interest of a given user in one category, related activities are scored and combined. Despite the categories defined in [32], this paper introduces more categories, providing the opportunity to have both accurate and explainable gift recommendations.

Moreover, the present study deals with the "giftability" of items which has been disregarded by other papers. Having a product curation team, a gift catalog consisting of 5000 different products is collected. To scale the aforementioned catalog, a gift rank algorithm is introduced to detect whether a product is giftable and how giftable it is. This algorithm takes into account features related to the product as well as features related to social data and activity surrounding it.

The proposed method by [46] utilizes microblog information from users on Sina Weibo to construct a user portrait for gift recommendation. The information collected from the website undergoes sentiment analysis to have its effective features representing preferences obtained. These features are, then, integrated with the user's gender, age, and location to build the user's portrait. Subsequently, the paper presents both an offline and a real-time recommendation method.

The proposed content-based real-time recommendation method uses tag-based techniques to suggest gifts. In summary, using the TF-IDF method, product tags are extracted from an e-commerce website, then, based on the intended gift recipient's portrait a list of related gifts is recommended. On the other hand, to address non-linear features, a collaborative filtering recommendation is proposed, established on the NeuralCF introduced by [47]. The intention to use a multilayer neural-based model is to have sufficient crossover as well as non-linear combinations. To feed the model in the training phase, users' portraits and gift profiles are embedded in vectors using the proposed representation by [48]. Finally, the trained model can be used as an offline recommendation system based on similar users.

The problem of gift recommendations for patient-visit is introduced by [49]. The recommended item in this setting should not only fulfill the demand for the nutrition of the patient but also be aligned with the intended gift recipient's preferences and information. The preferences of the patient are obtained from her click rates.

5.2.2 Pros and cons of the social media data methods

One of the advantages of using social media data for a gift recommendation is the abundance and fast-growing available data. To some extent, the gathered information to can determine the user's behavior and personality, as well as her interests.

Studies have shown that user's social media accounts can be used to predict some of their characteristics of them such as attachment style [50], also there are many available methods for obtaining personality traits of users through their online behavior [51]. Integrated with the demographical information obtained from the user's social media account, a comprehensive user profile is constructed. Therefore, compared to other methods, the rich user profiles built upon this method can provide the recommendation algorithm with a greater range of features.

Another advantage of these methods is the diversity that can be obtained using data gathered from a variety of people. Therefore, a wider range of users is considered in the recommendation technique. This can be valuable for those of the intended gift recipients with niche and unique interests.

However, there are also several challenges associated with this method. One major challenge is determining the accuracy of the obtained data. Fake profiles, online robots, and advertising content do also play their role in social media by manipulating or steering online trends. Moreover, some people might not reflect their true personality on their online accounts which might lead to inaccuracy of the user profile construction. Therefore, one of the difficulties of these methods is to determine and rely on genuine information for fair recommendations.

In addition, the problem of privacy is still presented in this method. Some users might be unwilling to share their account with a third-party application to base a recommendation on that. The methods that rely on Facebook profiles, for instance, should grant permission from the intended gift recipients to have their information shared with the platform.

5.3 Manually-entered data

In a method based on manually-entered data, the information related to the recipient is fed directly into the model. The information may contain demographical data, such as age and gender, as well as information about the recipient's preferences or personality. The assumption of this model is that the gift giver can provide some information about the recipient, which can capture her interests. Many of the methods in this section are based on chatbots that help gift-givers in order to either choose the gift directly or address the gift recipient's intention indirectly. However, there are some other methods that are not based on a chat system.

5.3.1 Review of the selected papers with manually-entered data methods

A rule-based framework via chatbots for gift recommendations is presented in [52]. The chatbot initials the intended gift recipient's profile by asking several multiple-option questions related to her gender and hobbies from the gift-giver. Subsequently, based on the gift-giver's responses, a gift is suggested.

First, a reference answer matrix linking items and categories to questions is manually constructed. Second, for each category i, a normalized popularity weight function $w'(\cdot)$ is constructed based on search frequency, e-commerce score, and dialog sessions. Third, Y_n^l, the importance of option l in the question

q_n, is obtained, and using the Shannon entropy for the multivariate Bernoulli distribution of options, the weight of each question q_n is defined. Finally, a policy-based reinforcement learning algorithm is used to train the chatbot based on the confidence of candidate items in each step.

The previously introduced algorithm is assessed based on accuracy and the number of asked questions [53]. If the theme of gift-giving, for example, Harry Potter is established, a gift is recommended through an average of 20 questions. However, a context-free recommendation takes about 47 questions for a recommendation. This is because the number of potential gifts is relatively lower in the first case. While in the second case, the number of gifts is 500, and since in the real-world setting the number of the products is higher, the presented technique is unscalable due to the number of asked questions and the process of the initialization of the database.

Somewhat similar to the proposed model by [52, 54] has proposed a chat-based model to enhance the consideration of gift-givers to various perspectives of the intended gift recipients through a set of questions. Unlike the previous model, the list of questions in this model is fixed, but it allows for keyword answers rather than preset choices. Once the gift giver has completed the questions, the model conducts a search based on the answers on an e-commerce website and suggests close items to the recipients.

In contrast to previous models, [31] proposed a novel model that is grounded in research indicating that recipients tend to appreciate gifts that match their personality [55]. The introduced collaborative filtering model utilizes the intended gift recipient's personality traits, as addressed by the Big Five Personality Test, in order to suggest an appropriate gift category through a fuzzy method on a list of inference rules. These inference rules are derived by two psychologists from the conducted survey results. Finally, based on characteristics of the gift recipient such as gender, age, hobbies, the moment of gift giving, and the available budget, a gift search is conducted on a list of the selected category.

Based on the concept of aroused affection through gift giving, [33] proposed a two-step hybrid gift recommendation system. This method breaks down the recommendation process into two steps: (1) What affection should the gift-giving experience arouse in the intended gift recipient, and (2) What gift arouses this affection in the recipient with a certain character. A decision tree and a KNN algorithm are trained on survey-collected data to solve this problem in two steps.

In the first step, a decision tree algorithm classifies gifts along with other variables such as motivation, givers' characters, etc. Through this approach, a gift is assigned to one or more categories such as functional, surprising, and warm. In the second step, the KNN ($k = 10$) algorithm is utilized to find the 10 best gifts in the class of the intended affection. Variables such as budget, recipient's character, scenario, the bond between the giver and recipient, etc. are utilized by the KNN algorithm in order to define closeness in the refined list.

Although no specific paper is dedicated to reviewing the gift recommendation system proposed by Amazon, it is worthwhile to discuss its approach based on available information and observations because Amazon is the biggest e-retailer in the United States [56]. The Amazon gift recommendation system is an example of a semi-personalized recommendation system. The gift-giver can only choose the intended recipient's age group from six predefined ranges and their gender from three categories. Moreover, the final results can be pruned based on the recommended item's category. The advance of this method lies in the variety and diversity of the gift catalog. By leveraging its user interactions database, the system can identify popular gift choices for different age groups and genders, ensuring a certain level of relevance in its suggestions. However, by focusing primarily on age and gender, the system may not capture the recipient's tastes and preferences fully. Consequently, some gift suggestions might not be as relevant or appreciated by the recipient.

5.3.2 Pros and cons of the manually-entered data methods

One of the advantages of gift recommendation methods that are based on manually-entered data is that they do not rely on predicting the recipient's attributes based on their available data. Instead, they obtain information directly from the gift-giver. This can be more accurate compared to other data acquisition methods in cases where the gift recipient is well-known to the gift-giver.

Another important advantage of these systems is that there are fewer to nothing privacy concerns regarding them. In comparison to other recommendation methods that require access to either the user's personal data in an e-commerce website or social media platform, these methods do not need to obtain or store any personal information. Thus, this approach is more privacy-friendly which is crucial while some individuals might be reluctant to give permission to access their personal data to third-party websites.

Despite these advantages, there are some limitations regarding these methods, one of them is that the accuracy of the recommendation is highly dependent on the quality and comprehensiveness of the information provided by the gift-giver; the recommendation may not be accurate, if the information is insufficient. Therefore, this approach might not be ideal for gift suggestions in which the relationship between the gift-giver and the gift recipient is not intimate. Additionally, some of the gift-givers might find working with chatbots or filling in information about the intended gift recipient time-consuming and tedious which can be a deterrent factor of this approach. Thus, selecting the complexity and the number of questions is one of the trade-offs of these models.

Another disadvantage of these methods is that they cannot fully capture the concealed preferences of the gift recipients. While the gift-givers may believe that they are aware of gift recipients' preferences, there are still some aspects that are overlooked [3] which can be found restrictive in the process of gift recommendation. In contrast, obtaining these concealed preferences from social media platforms or e-commerce websites help recommendation systems to address these intentions and can potentially increase the accuracy of the system.

In Table 2, an overview of technical and gift exchange assumptions alongside major findings and contributions of the selected papers are presented. This table facilitates a comparative analysis for researchers, allowing them to assess the strengths, weaknesses, and assumptions of each paper. Such a comparison aids in identifying research gaps within the existing literature. Moreover, a summary of the methods and approaches employed in the selected papers is offered in Table 3. Additionally, the adherence of the selected methods to the introduced framework is provided in Table 4.

6 Discussion

6.1 Theoretical contributions

This paper makes several contributions to the field of gift recommendation systems, offering valuable insights and paving the way for future studies. Firstly, this study is the first attempt to synthesize the gift recommendation systems' literature. In this research, we review the selected gift recommendation papers and discuss their methods and approach, survey their assumptions, and asses their advantages and disadvantages. The objective is to aid researchers in order to identify the research gaps and potentially make contributions to the literature terrain.

Secondly, this paper introduces a novel approach to categorizing gift recommendation systems, which enhances the readability of the literature review. Employing this approach provides a more structured and organized view of the terrain and the underlying advantages and disadvantages attached to any category.

The third theoretical contribution of this paper is offering a gift recommendation framework as a conceptual guide for evaluating and designing gift recommendation systems. The presented framework is backboned by the introduced metrics, namely, accuracy, privacy, and scalability. Accuracy is an essential metric to assess the quality of outputs of a gift recommendation system. It is entangled with the recommendation algorithm which is based on assumptions of the system. It can be evaluated through various methods such as user ratings, precision, recall, or even optimization-based approaches. However, direct comparison is challenging due to the absence of a benchmark and a ubiquitous dataset. Yet, relying on the attributes of the "recommended gift" is more promising because it unrolls the gift-giving presumption of each method.

Privacy is a significant concern in the online world. In the recommendation paradigm, privacy influences not only the user concerns but also the level of personalization these systems can achieve. Furthermore, privacy and data source considerations vary, as users' willingness to provide personal data differs and utterly based on the required degree of personalization and the type of accessed data.

Scalability is another important factor to consider in assessing gift recommendation systems; Fast and efficient recommendations increase user satisfaction with the system. Additionally, the operational cost of online recommendations is a concern; if a recommendation technique is costly or inefficient in operation, it may not yield favorable economic revenue or be feasible for a large-scale target market. Despite this importance, many of the proposed methods do not explicitly focus on this aspect. Nonetheless, there is a potential for these methods to incorporate scalability features to be implemented in a real-world scenario.

The proposed framework integrates these metrics to aid in the evaluation and design process of gift recommendation systems. It considers the accuracy of the

Table 2 Summary of methods employed in the selected papers discriminated by their main category

Paper	Technical assumptions	Gift Exchange assumptions	Major findings and contributions
[34]	Gift-giver and recipient share an e-commerce platform; giver knows recipient's profile. In addition, gift-exchange transaction data between users are stored on the website	Users sharing similar gift transactions tend to have common interests in gift preferences	Considering the gift recommendation as a group recommendation, modeling it with a graph, and addressing the problem with node-level and edge-level algorithms
[35]	Gift-giver and recipient share an e-commerce platform; giver knows recipient's profile. In addition, the platform collects demographic data	Past purchases capture gift preferences of the recipients	Considering the gift recommendation problem as an optimization task, and incorporating bio-inspired algorithms to solve it
[32]	Gift-giver and recipient possess Facebook accounts, which are authenticated within the app	Facebook posts, comments, and biography classify a user's gift interests into six sufficient and predefined categories	Classifying recipients and items into six categories, Considering the gift-exchange event
[36]	Gift-giver and recipient have Facebook accounts that are authenticated in the app	Facebook posts and comments can infer the affinity of a user which determines gift interest. "Gitability" of an item can be inferred by similar items	Considering the "giftability and price of an item, building a social genome for capturing high-level entities based on trends, etc., exploring explainability of recommendation
[46]	Gift-giver and recipient have Sina Weibo accounts that are authenticated in the app. In addition, they share enough microblogs on the platform	Microblogs of users capture their gift interests	Addressing non-linear features, utilizing tag-based methods
[49]	Gift recipient click behavior is recorded. In addition, this information is accessible to the recommendation system	The recipient's click rate reflects her gift exchange interests	Integrating gift exchange within a patient-visit scenario
[52]	A list of gifts can be established which captures many of the possible gifts, along with a set of questions about item features that are filled. Gift-giver can answer established questions about the recipient	The set of questions can determine the gift interests of the recipient if answered accurately	Considering the e-commerce score of items in the recommendation, utilizing a policy-based RL to train the chatbot
[33]	Gift-giver can answer questions regarding gift recipients and exchange intentions such as characteristics, hobbies, closeness, motivation, etc	Recipient's preference, closeness, and the intended aroused affection determine gift preferences	Considering the aroused affection in gift giving, taking into account giver recipient bond

Table 3 Summary of methods employed in the selected papers discriminated by their main category

Main Categories	Paper	Method	Approach
Costumer behavior data	[34]	CF	Multiplicative composition of edge level recommendation
	[35]	Hybrid	Two methods based on evolutionary programming along with a CF and CBF approach
Social media data	[32]	Hybrid	A hybrid method based on categorizing user profiles, gift-exchange events, and Pearson correlation of users and items
	[36]	Hybrid	Based on the social genome of the media trends regarding the "giftability" of items and profile categorization
	[46]	CBF	Tag-based real-time content-based recommendation in addition to neural-based collaborative filtering online method
	[49]	CBF	Recommendation based on patient's needed nutrition and her preferences
Manually-enterd data	[52]	KB	Chatbot recommendation based on a question-item database enforced by entropy-based question selection
	[33]	Hybrid	A two-step recommendation based on KNN and decision tree based on the aroused affection in gift giving

Table 4 Adherence of the selected papers to the provided framework with the accuracy, privacy and data source, and scalability metrics

Paper	Accuracy	Privacy & Data source	Scalability
[34]	Recall: 75%	Gift purchase history	✓
[35]	Precision: 80%	Purchase history and demography	✓
[32]	Accuracy: 67%	Facebook Account	✓
[36]	Precision: 97%	Facebook Account	✓
[46]	Not reported	Sina Weibo microblogs	✓
[49]	Not reported	Click behavior	✓
[52]	8-question accuracy: 24.5%	Manually-Entered	×
[33]	Precision: 81%	Manually-Entered	×

recommendation method regarding its adherence to the “recommended gift" attributes, privacy level with respect to its methodology in data acquisition, and scalability in relation to its produced model. By assessing these metrics, researchers can understand the system’s performance and effectiveness in providing accurate and personalized recommendations as well as its scalability for a market-size implementation, while considering privacy concerns. Moreover, this framework can enable researchers to make informed decisions during the development process; balancing personalization with privacy concerns, considering scalability, and deliberately setting the model assumptions can be achieved by utilizing this framework during the design.

6.2 Managerial insights

A literature review offers valuable insight to managers and practitioners by presenting a comprehensive analysis of studies centered on a single concept. Through this paper, we fulfilled this objective by surveying papers on gift recommendation systems. The proposed gift recommendation framework offers valuable guidance for businesses and organizations looking to implement a gift recommendation system; by focusing on accuracy, privacy, and scalability, managers can better understand the system’s gift-giving assumptions and its potential impact on user satisfaction.

A gift recommendation system may enhance the personalization in recommending more relevant gifts to customers which will facilitate their gift selection as well as enhance their satisfaction, delight, and engagement with the platform. Customers would be more likely to be pleased with a platform that could recommend gifts which found apt in the relationship considering attributes related to the gift-giving situation and gift recipient and giver. This not only makes the gift-giving process easier but promotes a stronger relationship between customers and the platform. Similarly, the e-commerce platforms will receive more conversion and sales if they recommend personalized and relevant gifts utilizing the proposed framework.

We found that the data acquisition method is the Achilles’ heel of gift recommendation systems. It not only impacts the system’s privacy but also influences its accuracy and scalability. Therefore, we suggest that firms conduct customer research in order to examine the extent to which target users are willing to share their data with a third-party gift recommendation system. This investigation can provide valuable insights in order to select an appropriate data acquisition method that balances privacy concerns along with overall performance. Moreover, we believe that these systems can be leveraged by separate data than which they recommend based on. For example, a gift recommendation system can be trained on data accumulated from social media by optimizing gift suggestions with users' attributes; however, the recommendation process can be addressed through the manually-entered data method. These distinctions can be helpful in diminishing privacy concerns while maintaining accuracy.

6.3 Policy implications

The paper's policy implications primarily revolve around the importance of privacy and data acquisition in gift recommendation systems. As these systems heavily rely on user data to provide personalized recommendations, data privacy, discrimination, and manipulation should be addressed as a concern.

As mentioned before, privacy is one of the concerns in gift recommendation systems that collect and use personal data about users. Thus, these recommendation systems may create a potential concern for regulatory bodies that strive to protect customer data and privacy. The stored data can be used to track users' activity, target them with advertising, influence their purchasing decisions, etc. In addition, the use of purchase history or social media data must be granted by users, as these sources can potentially reveal personal information about the targeted user. Therefore, Regulatory bodies should impose data protection and privacy regulation on gift recommendation systems. These regulations might require a transparent mechanism for collecting and using customer data. Moreover, these systems should obtain consent from intended gift recipients before accessing their data. Users also should have the option to limit or revoke previously-given access when they desire.

Discrimination and fairness in suggestions is another concern with recommendation systems. Because these systems are trained on social media or customer behavior data, which is predominated by certain races or ethnicities, minor groups might be marginalized by facing a major group-centric gift recommendation. Regulations can help to mitigate this bias in gift recommendations enabling a fair outcome for any person assigned with a certain gender, race, religion, or other attributes utilized in these systems such as personality traits.

Another important concern is decision manipulation through gift recommendations. With a biased or promoted recommendation, these systems can be used to manipulate users making them purchase items that are expensive or unnecessary. One approach to address this concern is to have gift recommendations tagging ads with certain keywords. In addition, to prevent biased recommendations, regulatory bodies can require a transparent and explainable recommendation algorithm from platforms.

7 Conclusion and future scope

In this review paper, our focus was on examining one of the subsection fields of e-commerce recommendation systems, the gift recommendation system. Through conducting a comprehensive search using relevant keywords and implementing a screening, papers were selected to be the base of our review paper. Throughout this review paper, we carefully addressed relevant findings of gift and gift exchange in psychological, marketing, and anthropological fields. Additionally, we offered a framework that could assess gift recommendation systems based on their accuracy, privacy and data source, and scalability. Subsequently, we defined a new categorization for dividing gift recommendation systems based on their recipient data acquisition method. The techniques are divided into three introduced categories: (1) Customer behavior data, (2) Social media, and (3) Manually-entered data. Moreover, we reviewed the papers under categories and addressed their advantages and limitations, moreover, we assessed the selected papers and their adherence to the provided framework.

Methods based on customer behavior data rely on purchase histories, ratings, wish lists, search patterns, etc. However, it is important to consider that purchase history may not reflect current needs or buyer satisfaction. Also, privacy concerns arise as accessing recipient data requires permission. Despite these limitations, customer behavior data remains valuable for personalized gift recommendations, as it provides insights not apparent through other means.

Methods that obtain data through social media rely on users' online accounts to analyze their interests. The presumption in these methods is that social profile reflects individuals' preferences. The abundance and diverse available-online data are considered the advantages of these methods. However, challenges include determining data accuracy and addressing users' privacy concerns. Users may not always represent their true selves online, and permission that is required for accessing their information may hinder individuals.

Manually-entered data gift recommendation methods obtain the recipient's information directly from the gift giver. The acquired data can range from demographic data to user preferences and personality traits. Sometimes these methods involve a chatbot which ought to gather relevant information in a user-friendly manner. The advantages of these methods are the minimal privacy concerns and the accuracy of the obtained data. However, limitations include the quality of the provided information, its time-consuming nature, and the inability to capture hidden preferences.

In summary, this study embarked on an exploration driven by the four aforementioned research questions regarding gift recommendation systems. Through our survey, we investigated evaluation metrics, introduced a gift recommendation framework, and explored assumptions and challenges within the terrain, among other aspects. In the following paragraphs, we issue the research questions in detail.

For Research Question 1, we reviewed other survey papers on e-commerce recommendation systems to identify metrics utilized for evaluating recommendation systems. We selected accuracy, privacy, and data source and scalability metrics, discussing their role in the context of gift recommendation systems. Furthermore, we investigated how these metrics are addressed in the gift recommendation literature. Consequently, we developed a framework for evaluating selected papers based on their adherence to this framework. The proposed framework suggests that the privacy of a gift recommendation system is related to its data acquisition method, the accuracy is based on the recommendation algorithm, and the scalability of the system is determined by the model.

In response to Research Question 2, we examined papers from other disciplines that highlight attributes of exchanged gifts. Based on these attributes, we introduce features for the "recommended gift". Considering these features facilitates comparing recommendation models since there is no benchmark dataset. Moreover, these features assist in determining the underlying gift-exchange assumptions of the models.

We summarized our findings in three tables in response to Research Question 3. Firstly, Table 2 illustrates the technical and gift-exchange assumptions, as well as the major findings and contributions of each model. Our survey revealed that using the same e-commerce website or having the social media account authenticated to the gift recommendation platform is presumed in many papers. Furthermore, sharing the same gift interest by similar users, and the ability to capture gift interests through social media posts is some of the gift exchange assumptions identified in the selected papers. In addition, the "major contribution or findings" column facilitates a comparative analysis for researchers in order to indicate research gaps within the literature. Secondly, Table 4 provides insight into the type of recommendation method employed in each paper, along with its approach. This table highlights the widespread use of Hybrid methods in the literature; however, it is noteworthy that the utilized approaches in these papers lack novelty, emphasizing the need to adopt new and innovative approaches in gift recommendation systems. Lastly, Table 2 summarizes the adherence of the selected papers to the framework by addressing the metrics incorporated within it.

Finally, addressing Research Question 4, we perceived that the most challenging aspect of gift recommendation systems is their method of acquiring the intended gift recipient information, as it is entangled with the privacy and the accuracy of the model. Furthermore, we examined the conventional categorization commonly used in the classification of recommendation systems. However, given that this categorization falls short to provide a deeper understanding of the literature, we proposed a new classification for gift recommendation systems which centers around the challenging aspect of gift recommendation systems.

Below, a brief summary of findings for each research question highlights key insights and contributions.

- Introducing a comprehensive evaluation framework based on accuracy, privacy, data source, and scalability metrics,
- Identifying attributes across disciplines and introducing "recommended gift" features,
- Highlighting assumptions, recommendation methods, and opportunities for innovations,

- And addressing the challenges in acquiring recipient's information and introducing a new categorization method.

Future research in the field of gift recommendation systems should focus on addressing several key areas. Firstly, the development of benchmark datasets would greatly facilitate the comparison of accuracy across different methods, allowing for more meaningful evaluations and advancements in the field. Additionally, exploring novel approaches to improve accuracy, such as incorporating advanced machine learning techniques or leveraging user-generated content, could enhance the effectiveness of gift recommendations.

Privacy concerns are another critical area for future research. Investigating the market interest and users' willingness in sharing their private information for a personalized gift recommendation is essential to guide the design and implementation of privacy-satisfying systems. If gift recipients are reluctant to share their personal information, methods that are based on social media data or customer behavior data are less attractive for future research. However, methods to balance personalized recommendations with robust privacy protection mechanisms would help eradicate user concerns and build trust for customers in these systems.

Scalability is also an important aspect that needs further investigation. Developing or adopting scalable recommendation algorithms that can handle large datasets efficiently would ensure that gift recommendation systems can satisfy increasing user demands and handle the fast-growing multidimensional data on items or users while providing real-time recommendations without disregarding accuracy.

Moreover, considering the cultural and social aspects of gift-giving practices could enhance the accuracy and relevance of recommendations. Additionally, it can help not to recommend non-giftable items to avoid faux pas in gift exchanges. Exploring how cultural norms influence gift preferences and recipient satisfaction assists the researchers in order to introduce society-adoptable recommendation methods.

The potential future research areas in gift recommendation systems can be summarized as follows:

- Developing benchmark datasets; facilitating the comparison of accuracy across different methods,
- Exploring and adopting cutting-edge approaches in recommendation systems in the gift recommendation literature,
- Investigating the market interest and users' willingness in sharing their private information for a personalized gift recommendation,
- Exploring and adopting methods to balance personalized recommendations with robust privacy protection mechanisms,
- Adopting scalable recommendation algorithms,
- And addressing the cultural and social aspects of gift-giving practices in these systems.

In conclusion, our review underscores the importance of data acquisition methods in gift recommendation systems and the need for a balance between accuracy, privacy, and scalability. We believe market research can accurately assess to what extent users want to share their private data for a personalized gift recommendation. All in all, in our opinion, a multi-source approach to acquiring data in a gift recommendation system is preferable. A recommendation system that is trained on social media data has many advantages such as the ability to highlight niche spots with its diverse information. However, obtaining data from the gift recipient can differ based on their privacy preferences. An intended gift recipient with a private profile might prefer to have her interests manually entered, while an intended gift recipient with an open-access profile may rather have her data acquired directly from her social media profile.

Declarations

Conflict of interest Authors declare that they have no conflicts of interest.

Ethical approval There are no human subjects in this article and informed consent is not applicable.

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