Expert Systems With Applications 226 (2023) 120131

Contents lists available at ScienceDirect

Expert Systems With Applications

journal homepage: www.elsevier.com/locate/eswa

A systematic review of value-aware recommender systems

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ARTICLE INFO

Keywords:
Systematic survey
Recommendation
Multi-stakeholder
Multi-objective
Business value
Profitability

ABSTRACT

Research on recommender systems (RSs) has traditionally focused on the design of systems capable of suggesting items of interest for users. However, often the most important expectation for RSs used in commercial applications is to improve the business performance of the organization. For this reason, alongside the growth of e-business, we have witnessed growing interest in value-aware RSs that, unlike traditional RSs, are designed to optimize the economic value of recommendations by considering the objectives of multiple stakeholders. In this paper, we provide a systematic literature review, following the PRISMA guidelines, specialized in value-aware RSs. We explore key commercial applications, main algorithms, value categories typically optimized, and the most commonly used datasets. Furthermore, we note limitations of the state-of-the-art approaches and identify future research directions.

1. Introduction

Recommender systems (*RSs*) help users make daily decisions (Ricci, Rokach, & Shapira, 2022). These systems are used in various applications, including e-commerce systems (Zhao, Zhang, Friedman, & Tan, 2015), news (Lu, Dumitrache, & Graus, 2020) and online streaming (Najafabadi, Shekarchizadeh, Nabiollahi, Khani, & Rastgari, 2021) services, and advertising platforms (Guo et al., 2021). To alleviate the problem of information overload (Bollen, Knijnenburg, Willemsen, & Graus, 2010), RSs recommend items of greatest interest for users to focus their attention on. Traditional recommendation models are designed to provide personalised recommendations relevant to the user (Ricci et al., 2022). To match customer preferences, an RS typically addresses a specific objective (Deshpande & Karypis, 2004), namely, minimizing the prediction error or maximizing the ranking quality.

However, although providing products and services to satisfy customers is a fundamental requirement for the sustainability of any business, an organization often decides to adopt a recommender to improve business performance (Jannach & Jugovac, 2019; Jannach & Zanker, 2022). For these reasons, in the past few years, there has been increased interest in *value-aware recommender systems* (*VARS*) (Burke et al., 2017). These systems are designed to optimise the *economic value* of recommendations by balancing the interests of multiple stakeholders (Burke, Abdollahpouri, Malthouse, Thai, & Zhang, 2019), i.e., consumers, providers, and organizations. Some examples of VARS include recommenders designed to maximise profits (Pei et al., 2019), increase user engagement (Wu, Wang, Hong, & Shi, 2017) and improve customer lifetime value (Han, Yu, Liu, Tang, & Zhang, 2019).

In this article, we present a systematic literature review on value-aware RSs based on the PRISMA guidelines (Page et al., 2021). Most surveys in the RS field have investigated related domains, such as multi-objective RS (Zheng & Wang, 2022), multi-stakeholder RS (Abdollahpouri et al., 2020), multi-criteria RS (Monti, Rizzo, & Morisio, 2021), context-aware RS (Raza & Ding, 2019), and attribute-aware RS (Chen et al., 2020). However, to the best of the authors' knowledge, no survey or review has focused specifically on value-aware RSs. Therefore, in this work, we aim to help academic researchers and industry stakeholders understand how VARS can be used to optimise value, the principal application domains, open challenges to be addressed, and future research directions.

The main contributions of this paper can be summarised as follows:

- we provide a systematic literature review based on PRISMA guidelines focused on VARS by discussing articles collected from different research streams;
- we describe the main value categories that are traditionally optimised by VARS and the technical approaches used in the design of VARS algorithms;
- we discuss the various application domains, the most commonly used datasets, and the main challenges and possible future research directions.

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https://doi.org/10.1016/j.eswa.2023.120131
Received 19 September 2022; Received in revised form 19 January 2023; Accepted 9 April 2023
Available online 18 April 2023

The remainder of this paper is organised as follows. In Section 2, we introduce the theoretical background and discuss related work. In Section 3, we present the methodology used for the systematic review. In Section 4, we report the results of this study. In Section 5, we discuss some open challenges and future research directions. Finally, Section 6 concludes the article.

2. Background and related work

In this section, we introduce RSs to provide some background concepts and discuss related work considering VARS' differences from other recommender classes that share similar characteristics.

2.1. Recommendation algorithms

RSs are algorithms designed to offer suggestions of items of interest for users (Ricci et al., 2022). Various service providers have deployed RSs in different domains, including e-commerce (Zhao et al., 2015), online streaming (Najafabadi et al., 2021) and news services (Lu et al., 2020). Users interact with these systems through various online sites whenever they are looking for a product to purchase, news to read, or a movie to watch. RSs help users evaluate a large number of alternatives (Bollen et al., 2010) by suggesting items that might be of the greatest interest. These suggestions are offered to the user in the form of a ranking of items (Ricci et al., 2022). The ranking is generated by algorithms that exploit information collected explicitly (e.g., item ratings) or implicitly (e.g., browsing behaviour, product reviews) from the user's interaction with the platform hosting the service (Ricci et al., 2022).

2.1.1. The recommendation problem

The recommendation problem can be formulated primarily in two ways, i.e., determining the degree of user interest in a particular item (*prediction problem*) or identifying a set of k items of interest to the user (*top-k recommendation problem*) (Deshpande & Karypis, 2004). Formally, in both cases, given a set $\mathcal{U} = \{u_1, \ldots, u_m\}$ of users and a set $\mathcal{I} = \{i_1, \ldots, i_n\}$ of items, a RS is designed to predict a matrix of scores $\hat{\mathbf{R}} \in \mathbb{R}^{m\times n}$ from a matrix $\mathbf{R} \in \mathbb{R}^{m\times n}$ of ground-truth preferences (Nikolakopoulos, Ning, Desrosiers, & Karypis, 2022; Ricci et al., 2022). Although it is always possible to order the predicted ratings to obtain a rank of k items for the user, algorithms are developed specifically for the prediction problem (e.g., matrix factorization Koren, Bell, & Volinsky, 2009) or for the top-k recommendation problem (e.g., sparse linear method Ning & Karypis, 2011). There are two main modes by which recommender systems are evaluated (Jannach & Jugovac, 2019; Jannach & Zanker, 2022), i.e., online A/B tests or offline evaluation. Online evaluation based on conversion rates (e.g., measuring how often a user chooses a recommended item) is the most direct method for evaluating the effectiveness of an RS (Jannach & Jugovac, 2019; Jannach & Zanker, 2022). However, these types of studies are often difficult in practice because they require access to existing systems with large user groups, where potentially risky testing can be performed that could impact the economic performance of service providers. Therefore, the evaluation of offline performance based on historical data is generally preferred to online testing (Jannach & Jugovac, 2019; Jannach & Zanker, 2022). For the prediction problem, where the algorithm tries to infer the rating for a given user and item, performance is traditionally evaluated by calculating the prediction error (e.g., mean absolute error and root mean square error) (Shani & Gunawardana, 2011). On the other hand, for the top-k recommendation problem, since the algorithm outputs a list of k items for the user, performance is typically evaluated using relevance or ranking metrics (e.g., precision, recall, and normalised discounted cumulative gain) (Shani & Gunawardana, 2011). Therefore, offline evaluation provides an indirect performance measurement (Jannach & Jugovac, 2019; Jannach & Zanker, 2022), potentially correlated with online metrics, which is used as a proxy for the latter.

2.1.2. Main classes of recommender systems

To suggest the most relevant items, RSs personalise recommendations (Ricci et al., 2022). Different users receive different recommendations according to their interests. Based on the type of personalization, recommender systems are often divided into different classes. One of the best-known taxonomies of recommender systems (Ricci et al., 2022) divides algorithms into *content-based filtering* (*CB*) (Lops, de Gemmis, & Semeraro, 2011), *collaborative filtering* (*CF*) (Su & Khoshgoftaar, 2009) and *hybrid systems* (*HS*) (Burke, 2002). CB systems (Lops et al., 2011) suggest items with characteristics similar to those with which the user interacted in the past. CF systems (Su & Khoshgoftaar, 2009) recommend items that other users with similar tastes have engaged with in the past. By contrast, HS systems (Burke, 2002) rely on a combination of the previous techniques. In addition, further distinctions can be made within this taxonomy. CF systems are traditionally divided into *neighbourhood* (Nikolakopoulos et al., 2022) and *model-based* (Koren, Rendle, & Bell, 2022) approaches. The former (Nikolakopoulos et al., 2022) recommend new items using user/item similarity criteria (e.g., user-based neighbourhood, item-based neighbourhood). The latter (Aggarwal, 2016; Amatriain, Oliver, Pujol, et al., 2011; Koren et al., 2022) learn a predictive model from historical ratings to make new recommendations (e.g., rule-based collaborative filtering, latent factors models).

2.1.3. Typical challenges in recommender systems

There are various advantages and disadvantages depending on the type of algorithm chosen (Ricci et al., 2022). For example, RSs may suffer to a greater or lesser degree from the cold-start problem (Lika, Kolomvatsos, & Hadjiefthymiades, 2014), which occurs whenever the amount of information available is insufficient to produce recommendations that effectively reflect the interests of new users and recommendations of new items that have not yet been engaged with by users. In particular, Mohamed, Khafagy, and Ibrahim (2019) CB methods are generally more robust to new item cold-start than are CF methods. However, CBs often produce recommendations of items that are highly similar to those engaged with thus far, preventing the user from discovering surprisingly relevant items. By contrast, HS methods can work well in cold-start settings; however, the computational cost is often very high, and it is difficult to produce an explanation of the rationale behind the recommendations.

2.2. Value-aware recommender systems

In this section, we introduce the economic concept of *value*. We also note the typical types of business value generated by recommendations. Next, we provide a chronological overview of *value-aware recommender systems*. These algorithms are designed to directly optimise various types of business value of recommendations for organizations.

2.2.1. An economic perspective on the concept of value

From early academic definitions in the mid-1950s, the term value has had multiple meanings, closely related to the application scenario considered. In early studies, Miles (1961) defines the concept of value by distinguishing use value, estimated value, cost, and exchange value. As reported in the author's research, use value is the ability to perform a certain function, i.e., considering a mobile phone, its use value is the ability to make a phone call. On the other hand, the estimated value is related to the sphere of attractiveness and desirability, e.g., a mobile phone with a colour display is more desirable than one with a black-and-white display. Cost value is related to the economic quantity used to produce an item, e.g., the cost to produce every component and assemble a mobile phone. Finally, exchange value is related to the increase in value over time, i.e., the mobile phone after ten years.

On the basis of these theoretical concepts, authors have proposed alternative definitions that focus on different factors. In some work (Anderson & Narus, 1998, 1999), the concept of the value of a product or service is related to the expected benefit that the buyer receives as a function of the price paid. For example, if the purchase of a product produces certain savings, the value lies precisely in the delta between the savings and the price paid. On the other hand, other works (Kotler, 2000; Neap & Celik, 1999; Zeithaml, 1988) define value according to customer perception. According to this interpretation, the value of a product or service is highly dependent on factors related to the emotional and sensory sphere of the customer. For two distinct customers, the same product might have a different value depending on the emotions/feelings it generates.

As can easily be inferred from the above considerations, the definition of value is not unique and may differ depending on the perspective considered. The value for the user/customer is often related to the concepts of quality and personalization, experience and trust, features, and benefits (Lindgreen & Wynstra, 2005; Rokeach, 1973). Moreover, the value for the producer/business is often linked to the loyalty relationship established with the customer and the economic results of sales (Best, 2013; Buttle, 2007; Doyle, 2000). Therefore, when business value is referred to in the literature, it represents the impact on the company's economic indicators (e.g., revenues, costs, margins, profits, and losses).

2.2.2. On the business value of recommendations

As discussed in the previous section, the concept of value has multiple definitions in the literature and is largely context dependent. In the field of RSs, a recent study by Jannach and Jugovac (2019) and Jannach and Zanker (2022) proposes a heterogeneous taxonomy based on five distinct definitions of business value that recommendations may generate:

- *Click-Through Rate (CTR)*: according to which the business value of recommendations is defined according to the number of user clicks;
- *Adoption and Conversion Rate*: according to which the business value depends on the degree of customer adoption of the system;
- *Sales and Revenue*: where business value is defined as a function of total sales of products and services;
- *Effects on Sales Distributions*: according to which the value depends on the effects of recommendations on the distribution of items sold;
- *User Engagement and Behaviour*: according to which the value depends on the customer's overall engagement with the platform.

As can easily be observed, the business value of recommendations depends on the application context (e.g., product recommendation, news, ads) and the company's business model (e.g., direct sales, rental, subscription). As a result, the value of recommendations could differ depending on, for example, whether the company sells physical products through e-commerce or sells a subscription service by streaming video content.

Some studies (Fleder & Hosanagar, 2007, 2009; Kwon, Han, & Han, 2020; Lee & Hosanagar, 2014, 2019) provide quantitative evidence by relating recommendations to specific types of value (e.g., sales and revenue, effects on sales and distribution). For example, in some research (Fleder & Hosanagar, 2007, 2009; Lee & Hosanagar, 2019), the effect of recommendations on the diversity of products sold is measured. According to the authors, a recommendation system would individually lead the user to increase or decrease the diversity of items purchased. However, on average, recommendations lead to an overall decrease in diversity in favour of the most popular items. On the other hand, with regard to the effect of recommendations on the overall sales volume, in the literature (Lee & Hosanagar, 2014), it is found that depending on the type of design (i.e., collaborative filtering, content-based), one algorithm could show higher performance than another. Furthermore, as found in more recent studies (Kwon et al., 2020), these two factors, namely, diversity and sales volume, are correlated. In particular, greater diversity correlates with higher purchase rates, average purchase amounts, and cross-purchase rates.

2.2.3. Introduction to value-aware recommender systems

Personalization has traditionally led RSs to focus on the user (Ricci et al., 2022). Indeed, if recommendations were not able to meet user needs, they would not be as successful. However, in real-world circumstances, in addition to suggesting items of interest, the reasons a service provider may want to implement a recommendation system vary (Jannach & Jugovac, 2019; Jannach & Zanker, 2022). As recently argued in research on *multistakeholder recommender systems* (*MSRS*) (Burke et al., 2019), RSs should consider the interests of multiple parties, known as stakeholders, to generate recommendations. In the MSRS literature, any entity that affects or is affected by the recommendations is referred to as a stakeholder, e.g., consumers who receive the recommendations, providers who supply items behind the recommendations, and organizations that manage the recommendation service. Depending on the perspective from which the MSRS is designed, recommendations will be generated to optimise the utility of one or more stakeholders. Within the multi-stakeholder taxonomy, a particular class of algorithms known as *value-aware recommender systems* (*VARS*) can be distinguished. VARS are systems that aim to directly maximise the economic value of recommendations. These include systems designed to increase sales, improve customer lifetime value, and optimise profitability.

The strategic goal of optimizing the value of recommendations emerged with the growth of e-business. The first studies in the VARS field (Mu-Chen Chen, Long-Sheng Chen, Fei-Hao Hsu, Yuanjia Hsu, & Hsiao-Ying Chou, 2007) date to 2007. These works propose several methodologies to generate more profitable recommendations to increase the business value of an organization. However, the first explicit reference to the term *value-aware* is found in the work of Amatriain and Basilico (2016). In their study, the authors introduce VARS as a future research direction for industrial applications. Research on VARS was subsequently brought to the attention of the academic community in *Workshop on Value-Aware and Multi-Stakeholder Recommendation* (*VAMS 2017*) (Burke et al., 2017). The workshop encouraged researchers to formulate a common vision on this emerging research area by inviting the submission of papers on various topics, including value-aware recommendations and multi-stakeholder recommendations. After VAMS 2017, there has been an increase in the number of specialised articles on VARS. Some studies have investigated how to design VARS using specific methodologies including post-processing approaches (Kompan, Gaspar, Macina, Cimerman, & Bielikova, 2021) and reinforcement learning algorithms (Pei et al., 2019). Other articles have proposed methodologies that aim to optimise value in certain application contexts, i.e., e-commerce (Pei et al., 2019), advertising (Zhao, Zhou, Ou, Xu, & Li, 2020), news (Wu et al., 2017) and others. Furthermore, other studies (Jannach & Adomavicius, 2017; Kompan et al., 2021; Panniello, Hill, & Gorgoglione, 2016) have investigated the main benefits and risks of using VARS in real-world circumstances, considering customer pricing preferences, the trade-off between profitability and accuracy, and the short- and long-term consequences for organizations.

2.3. Other classes of recommender systems and related works

Research on VARS is an emerging topic. However, other RSs have been proposed in the literature to solve related problems. The latter include the following:

- *Multi-Objective Recommender Systems* (Rodriguez, Posse, & Zhang, 2012): in which the system aims to produce recommendations that optimise several objectives (e.g. accuracy, novelty, diversity) simultaneously;
- *Multi-Criteria Recommender Systems* (Adomavicius, Manouselis, & Kwon, 2011): in which the system exploits a user's preferences on different item criteria (e.g., room cleanliness, location, safety) to provide better suggestions;
- *Multi-Stakeholder Recommender Systems* (Abdollahpouri & Burke, 2022): in which the system considers the interests of multiple stakeholders (e.g., consumers, suppliers, organizations) to generate recommendations;
- *Context-Aware Recommender Systems* (Adomavicius & Tuzhilin, 2011): in which the system uses contextual information (e.g.,

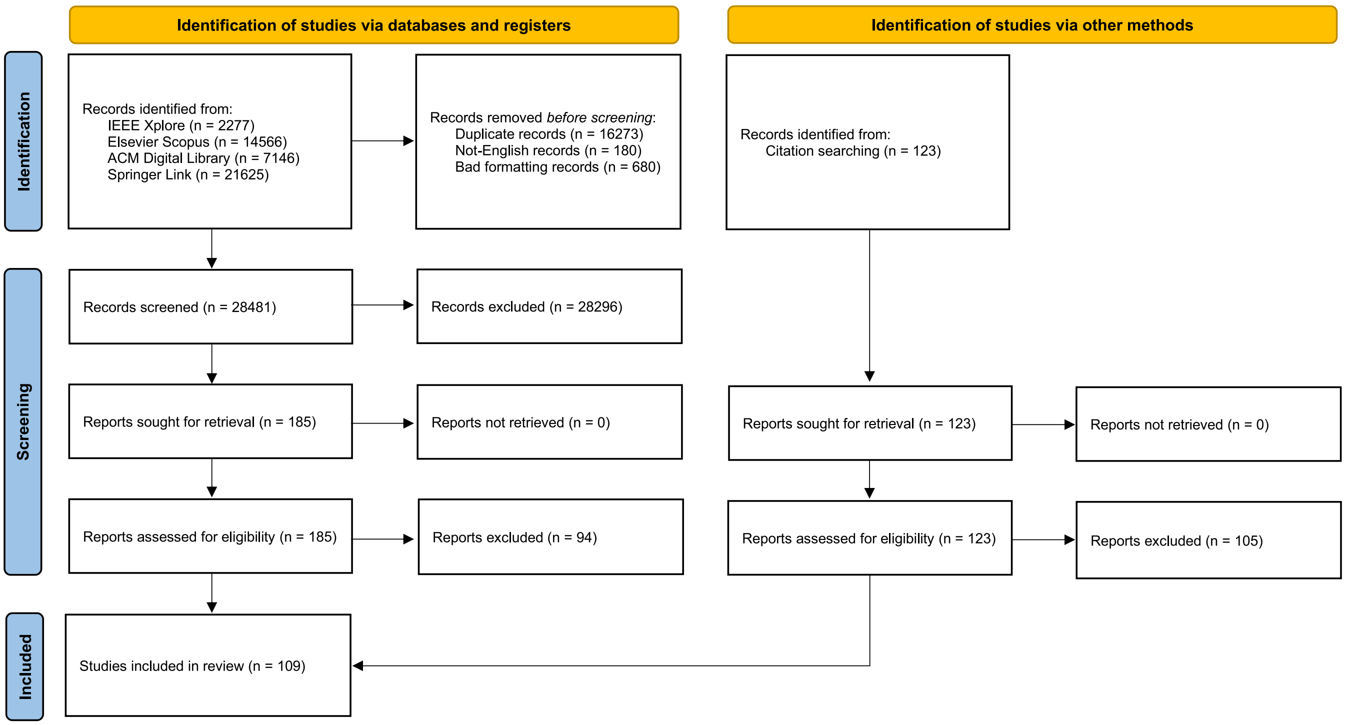

Fig. 1. PRISMA flow diagram.

location, time) to provide personalised recommendations to the user;

- *Attribute-Aware Recommender Systems* (Chen et al., 2020): in which the system exploits additional user (e.g., gender), item (e.g., category), and rating (e.g., time) information to provide more personalised recommendations;
- *Price-Aware Recommender Systems* (Zheng, Gao, He, Li, & Jin, 2020): in which the system exploits the user's price preferences and sensitivity to increase the accuracy of recommendations.

There are various surveys and reviews on RSs since the research field has been studied in the past several decades. Some of these works (Ko, Lee, Park, & Choi, 2022) approach the problem from a general perspective. Others specialise in certain topics, such as recommendations based on deep learning (Da'u & Salim, 2020; Wu, Sun, Zhang, Xie, & Cui, 2022) or reinforcement learning (Afsar, Crump, & Far, 2021). Many surveys focus on different types of RSs, such as multi-objective RS (Zheng & Wang, 2022), multi-criteria (Monti et al., 2021), multi-stakeholder (Abdollahpouri et al., 2020; Abdollahpouri & Burke, 2022), context-aware (Adomavicius, Bauman, Tuzhilin, & Unger, 2022; Raza & Ding, 2019), attribute-aware (Chen et al., 2020) and fairness (Pitoura, Stefanidis, & Koutrika, 2021; Wang, Ma, Zhang, Liu, & Ma, 2022). As introduced earlier, VARS differ from the previously mentioned categories since they aim to directly maximise economic value. To the authors' knowledge, although there is growing interest in the literature (Jannach & Jugovac, 2019; Jannach & Zanker, 2022) on the topic of RSs' value creation for business stakeholders, no surveys or reviews based on PRISMA guidelines (Page et al., 2021) focused on VARS have been conducted.

3. Methodology

To select studies for inclusion, we adopted the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) (Page et al., 2021) guidelines. The rigor and coverage of the PRISMA selection process is recognised throughout the scientific community as an indication of high reliability and quality. Below, we report the research questions behind the study, the information sources queried, the search strategy used to identify the articles, the eligibility criteria used for selection, the overall selection process, and the limitations of the study.

3.1. Research questions

The systematic review aims to answer the following research questions (RQ):

- RQ1: What are the main value categories typically optimised in value-aware recommender systems?
- RQ2: What are the main techniques used to design value-aware recommender systems?
- RQ3: What are the main applications of value-aware recommender systems?
- RQ4: What are the main datasets used in the literature of value-aware recommender systems?
- RQ5: What are the main state-of-the-art challenges and future research directions?

3.2. Eligibility criteria

Only articles that met the following eligibility criteria (EC) were included:

- EC1: Articles should focus on value-aware recommender systems.
- EC2: Articles must be in English and the full content of the article must be accessible by the authors.
- EC3: Articles must be unique, and any duplicate copies of the same article are not included.
- EC4: Articles must be peer-reviewed by journals or conferences.
- EC5: Graduate theses and doctoral dissertations are not included.

3.3. Search strategy

We identified all articles in various online journal databases from 2006 to 2022 resulting from the following search query (SQ):

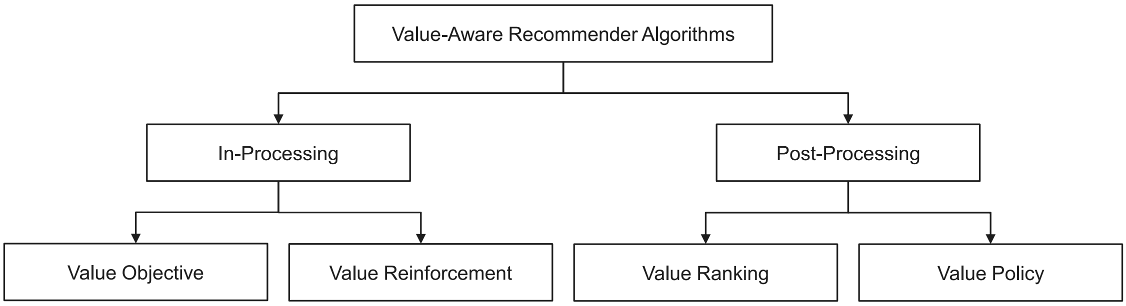

Fig. 2. Value-aware recommender algorithm taxonomy.

- SQ: *((“recommender system” OR “recommendation system”) AND (“value” OR “revenue” OR “sales” OR “click” OR “profit” OR “price” OR “customer” OR “product” OR “optimization” OR “maximization” OR “aware”))*.

To stay below the maximum number of items that could be extracted from the various databases, it was necessary to implement operational arrangements, i.e., breaking the search query into different subqueries, each executed in a distinct time range. Moreover, Harzing’s PoP software was used to avoid excessive delays in the retrieval of the title of ACM articles.

3.4. Selection process

As shown in the PRISMA flow diagram in Fig. 1, a total of 2277 articles from IEEE Xplore, 14,566 articles from Elsevier Scopus, 7146 articles from ACM Digital Library, and 21,625 articles from Springer Link were identified in this first research phase. We identified 16,273 duplicate records, 180 non-English articles, and 680 records that exhibited formatting problems in the title and metadata that were removed. In the screening stage, the titles and abstracts of 28,481 articles were analysed, and 28,296 records were excluded because the topics covered were not relevant to our study. A total of 185 articles were first sought for retrieval and then assessed for eligibility. At this stage, 94 articles were excluded after reading the full text. From this subset of eligible articles, an additional 123 articles were identified by searching for references in their bibliography, then sought for retrieval and finally assessed for eligibility. In this last stage, 105 records were excluded after reading the full text. At the end of this overall process, a total of 109 studies were included in the review.

3.5. Study limitations

The main limitations of the present study are as follows:

- Articles were selected primarily from IEEE Xplore, Elsevier Scopus, ACM Digital Library, and Springer Link and from reference searches in the bibliographies of articles that passed the screening stage.
- Unpublished articles, non-English articles, articles whose content was not accessible, graduate theses, doctoral dissertations, commercial products, and demos were not included.

4. Results

In this section, we present the results of the systematic review. First, we classify and describe VARS algorithms. Then, we review some of the work that has studied applications of VARS in the past few years. Finally, we present the most commonly used datasets.

4.1. Value-aware recommender algorithm taxonomy

In this section, we introduce the main algorithms in the literature on VARS. These algorithms leverage different technical approaches and, in some cases, depend on the nature of the recommended content. Although other taxonomies based, for example, on business KPIs or value dimensions, are available in the literature (see Section 2.2.2), we provide a classification of VARS according to the technical approaches used to highlight the different mechanisms underlying the various algorithms. As indicated in Fig. 2, VARS algorithms can first be divided into in-processing and post-processing based on the time at which value-driven optimization of recommendations occurs (although pre-processing methods may also exist, none have been found in the literature). Then, the approaches can be further divided into value objective, value reinforcement, value ranking, and value policy according to the specific technique used. In the following, we introduce each of these approaches.

4.1.1. Value-aware post-processing algorithms

Post-processing algorithms can be applied to any recommendation algorithm (treated as a black box) to optimise the value of recommendations

In traditional scenarios, a recommender system suggests to user u a rank $\mathcal{Y}^*_{u,k}$ of k items that maximises the expected interest:

$$\underset{\mathcal{Y}_{u,k}}{\operatorname{argmax}} \sum_{i\in\mathcal{Y}_{u,k}} \hat{r}_{u,i} \tag{1}$$

by sorting the predicted scores $\hat{r}_{u,i}$ of the unrated items in descending order and selecting the first k. Post-processing methods rely on predicted scores and other economic information to rerank the output of the original algorithm.

Value ranking

This class of methods extends the approach in Eq. (1) by incorporating economic value information into the objective function to rerank the output of the original algorithm.

Given a value $v_i \in \mathbb{R}$ associated with item i (e.g., product profit), a strategy commonly used by these systems (Azaria et al., 2013; Chen, Hsu, Chen, & Hsu, 2008; Das, Mathieu, & Ricketts, 2009; Demirezen & Kumar, 2016; Jannach & Adomavicius, 2017; Kompan et al., 2021; Lu et al., 2020; Malthouse, Vakeel, Hessary, Burke, & Fuduric, 2019; Mu-Chen Chen et al., 2007; Wang & Wu, 2009; Zhang, Chen, Wang, & Si, 2017) is to recommend the set $\mathcal{Y}^*_{u,k}$ of items that maximise the weighted expected interest:

$$\underset{\mathcal{Y}_{u,k}}{\operatorname{argmax}} \sum_{i\in\mathcal{Y}_{u,k}} \hat{r}_{u,i} \cdot v_i \tag{2}$$

selecting the first k items with the highest $\hat{r}_{u,i} \cdot v_i$. As noted in some studies (Chen et al., 2008; Mu-Chen Chen et al., 2007), in this way, it is possible to provide more profitable recommendations overall than those generated by a traditional RS at the cost of some reduction in accuracy. However, as noted in various works (Jannach & Adomavicius, 2017; Kompan et al., 2021; Malthouse et al., 2019), the interests of customers and organizations must be balanced appropriately. Clients may feel dissatisfied with a system that recommends only high-profit, irrelevant items, and the organization may risk losing loyal customers.

To mitigate this drawback, several studies (Azaria et al., 2013; Kompan et al., 2021; Lin et al., 2019; Lu et al., 2020; Nguyen, Dines, & Krasnodebski, 2017; Wu, Hu, Hong, & Liu, 2018; Zhang et al., 2017) have proposed simple extensions of Eq. (2) to account for the perspectives of different stakeholders and determine the best trade-off between economic value for the organization and customer interests:

$$\underset{\mathcal{Y}_{u,k}}{\operatorname{argmax}} \sum_{i \in \mathcal{Y}_{u,k}} (1-\alpha) \cdot \hat{r}_{u,i} + \alpha \cdot v_i \tag{3}$$

using a regularization parameter $\alpha \in [0,1]$ to control the equation. Some variants (Das et al., 2009; Demirezen & Kumar, 2016; Malthouse et al., 2019; Wang & Wu, 2009) of the approach in Eq. (3) have also used constraints to match certain conditions such as the user budget.

Value policy

Advanced post-processing approaches that are more complex than simple value ranking have also been proposed. We refer to these methods as value policies to indicate that they are based on specific policies consisting of multiple steps to optimise the economic value derived from the entire recommendation process.

Various studies (He, Liu, Zhao, Liu, & Tang, 2022; Hosanagar, Krishnan, & Ma, 2008; Li & Lakshmanan, 2014) have proposed multiple-step process-based approaches to optimise economic value. For example, one study (Hosanagar et al., 2008) proposed an algorithm that recommends relevant items to gain customer trust and then recommends profitable items once trust is gained to increase business value. More sophisticated models have also been studied (Li & Lakshmanan, 2014) by incorporating various factors such as price, profitability, product competition, and saturation effects to improve profitability over a finite time horizon. Recent work (He et al., 2022) has proposed a probabilistic approach to optimise multiple strategic parameters (e.g., click-through rate, user engagement) one at a time considering that optimizing one parameter could have positive effects on other value indicators as well.

Other works (Beladev, Rokach, & Shapira, 2016; Kamishima & Akaho, 2011; Najafabadi et al., 2021; Zhao et al., 2015) have proposed methodologies optimizing the value of recommendations by integrating dynamic pricing algorithms. For example, some works (Kamishima & Akaho, 2011) have proposed to optimise the discount of recommended items by exploiting multi-armed bandits. By contrast, a more recent work (Najafabadi et al., 2021) has proposed personalizing the price of recommended products based on customer willingness to pay to simultaneously optimise service provider profit and customer surplus.

4.1.2. Value-aware in-processing algorithms

While the methods presented above optimise value after the learning process, in-processing algorithms aim to modify existing or to introduce new algorithms to generate recommendations that optimise value without the need to perform subsequent operations.

Value objective

This class of methods contains algorithms that integrate the objective function of known or domain-specific algorithms to generate more valuable recommendations.

For example, some work (Cai & Zhu, 2019; Park, 2013; Park & Tuzhilin, 2008; Vargas & Castells, 2014) has proposed modifying the well-known *neighbourhood recommender system* (Nikolakopoulos et al., 2022). The original algorithm computes the similarity between users (*user-based approach*) or items (*item-based approach*) belonging to a given neighbourhood to predict the scores. A neighbourhood refers to a set of users who share similar interests or a set of items that have been engaged with by similar users. For example, in the user-based approach, the algorithm computes the similarity $sim(u,v)$ between a user $u \in \mathcal{U}$ who did not express a preference for item i and a user v belonging to a set $\mathcal{P}(u,i)$ of users who expressed preferences similar to u and rated i. Then, the algorithm infers the rating $\hat{r}_{u,i}$:

$$\hat{r}_{u,i} = \sum_{v \in \mathcal{P}(u,i)} sim(u,v) \cdot r_{v,i} \tag{4}$$

based on the ratings of the neighbours. Some value objective algorithms have been proposed by partially modifying the function in Eq. (4) to optimise some types of economic value. For example, some work (Cai & Zhu, 2019) has proposed a neighbour selection algorithm to increase the overall profitability of recommended products while maintaining accuracy under shilling attacks, i.e., identifying malicious users who generate biased ratings to influence recommendations for their own interests. Moreover, other studies (Vargas & Castells, 2014) have proposed increasing sales diversity by recommending users to items by reversing the original neighbour computation algorithm.

Furthermore, other research (Ge et al., 2019; Ho, Chiang, & Hsu, 2014; Wang & Zhang, 2011; Zhang et al., 2016; Zhao, Zhang, Zhang, & Friedman, 2017) extends the well-known *matrix factorization* algorithm (Koren et al., 2009, 2022) by incorporating value information into the objective function. In the traditional matrix factorization algorithm, the user–item interaction matrix $\mathbf{R}$ is decomposed into the product of two rectangular lower-dimensional latent space matrices representing users and items. Decomposition is often performed using a dimensionality reduction algorithm known as singular value decomposition (Wall, Rechtsteiner, & Rocha, 2003). The algorithm estimates the score:

$$\hat{r}_{u,i} = \mathbf{p}_u^{\intercal} \mathbf{q}_i \tag{5}$$

by computing the dot product between the l-dimensional latent feature vector $\mathbf{p}_u \in \mathbb{R}^l$ of user u and $\mathbf{q}_i \in \mathbb{R}^l$ of item i. Some value objective algorithms have been proposed by incorporating other factors into the calculation of predicted scores in Eq. (5) to optimise certain types of economic value. For example, some works (Ge et al., 2019; Wang & Zhang, 2011; Zhang et al., 2016; Zhao et al., 2017) have used predicted scores determined via matrix factorization and other economic information to improve the utility of recommended products to the user.

Value reinforcement

Recent studies have proposed value-aware recommendation algorithms by exploiting *reinforcement learning* (*RL*) (Sutton & Barto, 2018) techniques, a learning approach that aims to automatically learn an optimal policy based on the sequential interactions between an agent and the environment through trial and error to maximise a reward. An RL environment can be formalised through a *Markov decision process* (*MDP*) in the tuple $(\mathcal{S}, \mathcal{A}, \Omega, \mathbb{P}, \gamma)$, where $\mathcal{S}$ is a set of possible states, $\mathcal{A}$ is a set of possible actions, Ω is a reward function, $\mathbb{P}$ is the probability of transition from one state to another following an action and $\gamma \in [0,1]$ is a discount factor. Typically, in RL algorithms, an agent interacts with the environment to maximise the expected discounted cumulative reward:

$$\begin{gathered} \max \quad \mathbb{E}[\Omega(\tau)] \\ \Omega(\tau) = \sum_{t=0}^{\tau} \gamma^t \cdot \omega(a_t, s_t) \end{gathered} \tag{6}$$

with $\omega(a_t, s_t)$ as the reward for taking action $a \in \mathcal{A}$ in state $s \in \mathcal{S}$ at time t. The objective of the algorithm is to determine an optimal policy $\pi(a|s)$ that involves taking an action in a given state to maximise the reward.

Given the sequential nature of user interaction with an RS, *reinforcement learning recommender systems* (*RLRS*) (Afsar et al., 2021) have emerged as alternative approaches based on RL techniques to generate recommendations. Much of the literature on VARS (Guo et al., 2021; Han et al., 2019; Ji, Qin, Han, & Yang, 2021; Ju, 2017; Li et al., 2021; Pei et al., 2019; Theocharous, Thomas, & Ghavamzadeh, 2015; Wu et al., 2017; Zhao et al., 2020; Zheng et al., 2018; Zou et al.,

Table 1
Application domains of value-aware recommender systems.

Application domain	Most frequently used technique	Typically optimised value	Details
Product recommendation	Value objective	Sales and revenue	Table 2
Advertising recommendation	Value reinforcement	Sales and revenue	Table 3
News recommendation	Value reinforcement	CTR, User engagement	Table 4
Media recommendation	Value objective	Distribution	Table 5

2019) exploits this methodology to maximise the long-term value of recommendations, implementing the agent reward function $\Omega(\tau)$ in Eq. (6) to take into account the value $\mathbf{v}$ of the recommended items. For example, in one study (Theocharous et al., 2015), an algorithm was designed to maximise the customer lifetime value (CLV), i.e., the total value generated by the customer throughout his or her history. By contrast, in another study (Pei et al., 2019), the reward function was modified via the concept of click-conversion rate (CVR) to generate recommendations that maximise the economic value from each user action (e.g., click, add-to-cart, pay).

4.2. Value-aware recommender systems applications

Recent years have witnessed growing interest in VARS. Since algorithms are often designed based on domain-dependent characteristics, in this section, we review the literature on VARS in various application domains. As indicated in Table 1, these include the recommendation of products, advertising, news and media. This analysis is proposed because each type of application has distinctive characteristics that lead to a preference for certain methodologies and for optimizing certain types of economic value. The following sections refer to the detailed tables linked to the main table for a more in-depth discussion of individual research works.

4.2.1. Product recommendation

Many VARS have been developed to optimise product sales. Below, we provide an overview of the main topics addressed in the literature, including the accuracy-profitability trade-off, the optimization of multiple objectives simultaneously from a multi-stakeholder perspective, the usefulness of recommendations for the customer, the long-term implications of value-aware recommendations, the influence of price on the willingness to pay, and real-world studies.

Table 2 summarises the literature on value-aware product recommendation systems.

Accuracy-profitability trade-off

Business interest in leveraging recommender systems to increase revenue or other key performance indicators of global e-tailers existed since the 2000s. In early work, Chen et al. (2008) and Mu-Chen Chen et al. (2007) proposed a methodology to weight the recommendations of a collaborative filtering algorithm with product profitability factors (i.e., revenues minus costs). This approach allows the system to meet the customer's needs and achieve higher profit margins for the organization. However, as observed by the authors, focusing excessively on profitability could rapidly degrade the accuracy of recommendations. While some techniques based on constrained optimization (Akoglu & Faloutsos, 2010; Das et al., 2009; Hammar, Karlsson, & Nilsson, 2013; Li & Lakshmanan, 2014; Wang & Wu, 2009) or multi-objective algorithms (Aridor & Gonçalves, 2022; Cai & Zhu, 2019; Desirena, Diaz, Desirena, Moreno, & Garcia, 2019; Ghanem, Leitner, & Jannach, 2022; Gu et al., 2020; Huang, Chen, Huang, & Huang, 2013; Lin et al., 2019; Louca, Bhattacharya, Hu, & Hong, 2019; Ma, Li, Cen, & Arora, 2019; Nguyen et al., 2017) have been proposed (see Section 4.1) to balance the potentially conflicting interests of multiple stakeholders simultaneously, other studies (Ghanem et al., 2022; Jannach & Adomavicius, 2017; Kompan et al., 2021; Zhou & Zou, 2022) have investigated the accuracy-profitability trade-off through offline simulations. As argued by Jannach and Adomavicius (2017), the items that are most important for the user may not be those that produce the highest business value for the service provider. Biasing algorithms in the direction of higher profitability could actually increase marginality while maintaining the relevance of recommended products. However, above a certain threshold, the probability of purchase drops dramatically, and the business value generated as a result is reduced. Taking this reasoning to its logical consequence, Zhou and Zou (2022) argue in a theoretical study that a profit-based recommender system could influence a marketplace by leading sellers to strategically increase product prices to compete in recommendations, leading to a decrease in overall profitability.

On the usefulness of customer recommendations

In contrast to previous studies, a different research perspective (Ge et al., 2019; Wang & Zhang, 2011; Yang, Xu, Jones, & Samatova, 2017; Zhang et al., 2016; Zhao et al., 2017) finds that the usefulness of customer recommendations is directly proportional to the sales performance of the recommendation system. In fact, according to leading economic theories, a rational customer would choose products that maximise their utility. Based on this perspective, Wang and Zhang (2011) develop a recommendation algorithm that maximises the net marginal utility of recommended products for the customer by exploiting the economic principle of diminishing marginal utility. Yang et al. (2017) propose an adaptive association rule mining algorithm to recommend the highest utility products. By contrast, Zhang et al. (2016) design a recommendation system that jointly optimises the interests of customers and sellers in an online marketplace. The system optimises customer surplus, defined as the amount of utility that a customer obtains with respect to the price that he or she pays, and producer surplus, defined as the amount of revenue that a producer obtains after costs. Further developing previous approaches, Zhao et al. (2017) propose maximizing the usefulness of recommendations based on the concept of the marginal rate of substitution. The algorithm considers the complementarity and substitutability of the products to be recommended to the customer compared to those already purchased. Finally, Ge et al. (2019) aim to optimise the utility of recommended products by maximizing the marginal utility per dollar (MUD) under customer budget constraints.

Long-term implications of value-aware recommendations

Thus far, the discussed works have focused mostly on optimizing short-term sales performance. However, as argued by Ghanem et al. (2022) and Jannach and Adomavicius (2017), the performance of an RS also depends to a large extent on the long-term effects of recommendations on customers. Purely profit-oriented strategies are overly biased towards the organization's short-term interests and can lead to long-term customer churn. Instead, strategies that balance profit with customer utility, and thus are more oriented to the customer's perspective, would likely lead to sustained profitability in the long run due to more stable levels of customer satisfaction. Hosanagar et al. (2008) considered this factor by arguing that a recommendation system should first try to maintain a certain level of trust by proposing products that are relevant to the customer before optimizing profitability. Additional work by Liu and Shih (2005a, 2005b), Shih and Liu (2005, 2008) and Tabaei and Fathian (2012) proposed methodologies based on customer lifetime value (CLV), a popular metric in the marketing and management literature that measures the overall value that a customer generates for the organization throughout his or her history. However, previous studies focused on the use of CLV to improve the quality of

Table 2
Product value-aware recommender systems.

Reference	Technique used	Optimised value	Dataset
Mu-Chen Chen et al. (2007)	Value ranking	Sales and revenue	Foodmart
Chen et al. (2008)	Value ranking	Sales and revenue	Foodmart
Hosanagar et al. (2008)	Value policy	Sales and revenue	N/A
Wang and Wu (2009)	Value ranking	Sales and revenue	Self-collected
Das et al. (2009)	Value ranking	Sales and revenue	N/A
Akoglu and Faloutsos (2010)	Value objective	Sales and revenue	N/A
Kamishima and Akaho (2011)	Value policy	Sales and revenue	MovieLens
Wang and Zhang (2011)	Value objective	User engagement	Self-collected
Jiang and Liu (2012)	Value objective	Sales and revenue	Self-collected
Huang et al. (2013)	Value objective	Sales and revenue	Foodmart
Hammar et al. (2013)	Value objective	Sales and revenue	Self-collected
Li and Lakshmanan (2014)	Value policy	Sales and revenue	Self-collected
Zhao et al. (2015)	Value policy	Sales and revenue	Self-collected
Jiang, Shang, Liu, and May (2015)	Value policy	Sales and revenue	Self-collected
Beladev et al. (2016)	Value policy	Sales and revenue	Self-collected
Panniello et al. (2016)	Value policy	Sales and revenue	Self-collected
Zhang et al. (2016)	Value objective	User engagement	Self-collected
Zhao et al. (2017)	Value objective	User engagement	Self-collected
Jannach and Adomavicius (2017)	Value ranking	Sales and revenue	MovieLens
Yang et al. (2017)	Value objective	User engagement	Foodmart, ChainStore, Amazon review
Ju (2017)	Value reinforcement	Sales and revenue	Dunnhumby
Nguyen et al. (2017)	Value ranking	Sales and revenue	Self-collected
Cai and Zhu (2019)	Value objective	Sales and revenue	Book-Crossing
Hosein, Rahaman, Nichols, and Maharaj (2019)	Value objective	Sales and revenue	MovieLens
Louca et al. (2019)	Value objective	Sales and revenue	Self-collected
Ma et al. (2019)	Value objective	Sales and revenue	SPMF/Retail
Ge et al. (2019)	Value objective	User engagement	Amazon review
Pei et al. (2019)	Value reinforcement	Sales and revenue	REC-RL
Desirena et al. (2019)	Value ranking	Sales and revenue	Self-collected
Lin et al. (2019)	Value objective	User engagement	EC-REC
Gu et al. (2020)	Value objective	User engagement	JD
Brodén, Hammar, Nilsson, and Paraschakis (2020)	Value reinforcement	Sales and revenue	Self-collected
Kompan et al. (2021)	Value ranking	Sales and revenue	Self-collected
Basu (2021)	Value policy	Sales and revenue	Self-collected
Li et al. (2021)	Value reinforcement	Sales and revenue	Self-collected
Ji et al. (2021)	Value reinforcement	User engagement	Self-collected
Aridor and Gonçalves (2022)	Value policy	Sales and revenue	N/A
Cavenaghi et al. (2022)	Value ranking	CTR	Self-collected
Ghanem et al. (2022)	Value ranking	Sales and revenue	MovieLens
Lee, Nam, Han, and Cho (2022)	Value objective	Sales and revenue	Self-collected
Zhou and Zou (2022)	Value policy	Sales and revenue	N/A

recommendations rather than to optimise the long-term value for the organization. More recent works (Brodén et al., 2020; Hosein et al., 2019; Ju, 2017; Li et al., 2021; Pei et al., 2019) have proposed directly optimizing the long-term performance of recommender systems by exploiting probabilistic approaches (Hosein et al., 2019) or reinforcement learning (Brodén et al., 2020; Ju, 2017; Li et al., 2021; Pei et al., 2019) algorithms (see Section 4.1). The latter have been used, for example, to maximise the cumulative value obtained via all user actions (i.e., click, add-to-cart, pay) (Pei et al., 2019) or to optimise customer lifetime value in cold-start scenarios (Ji et al., 2021).

Static vs. dynamic pricing

The majority of research on VARS is based on algorithms that keep prices static. However, a pioneering alternative approach is represented by systems that integrate recommendations with dynamic pricing algorithms (Beladev et al., 2016; Huang et al., 2013; Jiang & Liu, 2012; Kamishima & Akaho, 2011; Zhao et al., 2015). According to this philosophy, Kamishima and Akaho propose a system that strategically adjusts the price of items recommended to customers through a discount based on the type of customer visiting the system. If the customer would purchase the product at a discounted price, the system would propose a favourable price to obtain additional revenue. A different approach was proposed by Jiang et al. (2015), who designed a system that recommends products and simultaneously optimises associated promotional discounts to maximise the total profit gain for the company. Instead, Jiang and Liu (2012) optimise the discount of promotional products to increase the overall profitability of non-promotional products. The authors propose exploiting intra/cross-category effects of products purchased at a discounted price to stimulate customers to purchase non-discounted products. Additionally, regarding personalised promotions, Zhao et al. (2015) propose customizing the discount of recommended products based on customer willingness to pay predictions, while Beladev et al. (2016) propose recommending product bundles by pricing them to maximise the organization's revenue.

Real-world studies

Some research has studied the performance of VARS in real-world environments. In particular, the model designed by Hosanagar et al. (2008) has been used in many research works. The algorithm was designed according to the following assumptions: when a customer trusts an RS, the system biases the recommendations to increase profitability; when customer trust is below a certain threshold, the system recommends the most relevant products to restore trust at the expense of profitability. Some online studies (Basu, 2021; Panniello et al., 2016) used this algorithm to study the sales performance of a profit-based recommender system. In particular, Panniello et al. (2016), in a randomised field experiment, showed that the Hosanagar et al. algorithm achieved higher revenue than that of a content-based algorithm without affecting the customer's trust in the organization. In another experiment, Basu (2021) found that the relevance of recommendations and customer trust in the organization were positively correlated with the revenue generated from recommendations.

Similar results were reported by Kompan et al. (2021) in a study based on a real-world e-commerce dataset in the fashion domain. Integrating product profit factors and customer price preferences into the

Table 3
Advertising value-aware recommender systems.

Reference	Technique used	Optimised value	Dataset
Theocharous et al. (2015)	Value reinforcement	User engagement	Self-collected
Zhang et al. (2017)	Value ranking	Sales and revenue	Self-collected
Long, Wong, and Wei (2018)	Value policy	Sales and revenue	Package, NBA
Malthouse et al. (2019)	Value ranking	Sales and revenue	Self-collected
Han et al. (2019)	Value reinforcement	Sales and revenue	MovieLens
Zhao et al. (2020)	Value reinforcement	User engagement	Self-collected
Guo et al. (2021)	Value reinforcement	Adoption	Self-collected
He et al. (2022)	Value policy	All values	Amazon review

algorithms could actually increase the profitability and, in some cases, even the accuracy of the recommendations. However, an excessive bias could lead to opposite effects. Moreover, as argued by Cavenaghi et al. (2022), the price and rank position of a recommended product are two key factors that can influence CTR and other business value indicators.

4.2.2. Advertising recommendation

Several value-aware systems have been proposed to optimise the value of advertising. In the following, we provide an overview of traditional systems in this field and recent perspectives that aim to optimise customer lifetime value.

Table 3 summarises the literature on value-aware advertising recommendation systems.

Traditional advertising strategies

In advertising systems, sponsored space is traditionally sold through auctions, where different advertisers compete for customers' attention. The systems often work as follows (Aryafar, Guillory, & Hong, 2017; Feng et al., 2019; Guo et al., 2021): the advertiser first defines a subset of potential target customers based on certain demographic and/or purchasing characteristics; subsequently, he or she selects an objective to optimise through sponsored recommendations (e.g., number of clicks, add-to-carts or gross merchandise volume); finally, the advertiser defines a bid price that he or she will pay when the objective is reached. Therefore, a common strategy used by service providers to maximise system revenues is to sort advertisers' products into sponsored space by weighting the bid price by click-through rate or click-conversion rate. As a result, much of the literature in the field of computational advertising (Aryafar et al., 2017; Chapelle, Manavoglu, & Rosales, 2014; Feng et al., 2019; Graepel, Candela, Borchert, & Herbrich, 2010; He et al., 2014; McMahan et al., 2013; Ouyang et al., 2019; Zhou et al., 2018) investigates algorithms to predict the previous metrics as accurately as possible from the characteristics of the recommended items. Early work (Graepel et al., 2010) by Microsoft proposed a Bayesian algorithm based on a probit regression model to predict CTR in a Microsoft Bing sponsored search. Subsequent work describes the ad systems of Google (McMahan et al., 2013), Facebook (He et al., 2014) and Yahoo (Chapelle et al., 2014), as well as the algorithms used to estimate CTR. More recent approaches proposed by Etsy (Aryafar et al., 2017) and Alibaba (Feng et al., 2019; Ouyang et al., 2019; Zhou et al., 2018) leverage ensemble learning models and neural networks, respectively, to make predictions by exploiting features associated with items (e.g., text and images), and customer purchase behaviour.

Considering user interest to generate higher returns

Although conventional advertising strategies are widely adopted, alternative approaches have been proposed to optimise other aspects of advertising, particularly considering users' interests (Long et al., 2018; Malthouse et al., 2019; Zhang et al., 2017). Indiscriminately promoting high-profit items that do not match users' interests could push users away from the system. Thus, to consider both the interests of the organization and the users, Zhang et al. (2017) proposed a methodology to balance the revenue generated from the ads of an app store and the overall quality of the recommendations. The system optimises, in the same objective function, the profit from downloading financially sponsored apps and the number of downloads of non-sponsored apps relevant to the user. Adopting a similar perspective: Long et al. (2018) developed an algorithm that optimises the overall profitability of a promotional campaign while maintaining a certain number of satisfied customers; Malthouse et al. (2019) proposed a multi-stakeholder advertising system that jointly optimises ad revenue and user utility. Considering the user's interests in recommendations would increase customer lifetime value and improve other drivers of business value. However, as noted by He et al. (2022), maximizing multiple strategic parameters in the same objective function (e.g., click-through rate, user engagement) could lead to suboptimal results in individual indicators. Instead, considering that many indicators are interrelated, by adopting a probabilistic optimization methodology, optimizing one parameter at a time could have positive effects on other business values as well.

Maximizing customer lifetime value and advertiser revenue

As previously observed, the interests of multiple stakeholders should be balanced appropriately to maximise customer lifetime value. Trying to increase short-term profitability with overly biased recommendations could negatively impact an organization's reputation. If the trust relationship is broken, some customers may decide to purchase from competitors, and the company may lose valuable sources of revenue. To address this problem, some works (Guo et al., 2021; Han et al., 2019; Theocharous et al., 2015; Zhao et al., 2020) have studied how to optimise the performance of a long-term advertising system. Instead of recommending to customers ads that have the highest probability of being clicked, Han et al. (2019) and Theocharous et al. (2015) proposed leveraging reinforcement learning techniques to optimise customer lifetime value and, more generally, cumulative reward for the platform. Zhao et al. (2020) further adapted the approach in the case of sequential recommendations by proposing an approach that maximises cumulative user engagement by balancing longer browsing sessions and the click-through rate.

Moreover, from a multi-stakeholder perspective, in addition to the interests of service providers and customers, the system should consider the interests of advertisers. According to the latter perspective, Guo et al. (2021) proposed a system based on multi-armed bandits to recommend the best advertising strategy to advertisers. The system aims to encourage the adoption of the platform by helping advertisers define customer targets and bid prices to improve the performance of marketing campaigns by reducing the cost of trial and error.

4.2.3. News recommendation

Some value-aware recommenders have been proposed to optimise the value of news systems. Below, we provide an overview of conventional news recommendation strategies, the existing relationship between click-through rate and user engagement, and the optimization of long-term metrics to generate greater returns for the service provider.

Table 4 summarises the literature on value-aware news recommendation systems.

Table 4
News value-aware recommender systems.

Reference	Technique used	Optimised value	Dataset
Li, Chu, Langford, and Schapire (2010)	Value reinforcement	CTR, User engagement	Self-collected
Besbes, Gur, and Zeevi (2016)	Value ranking	CTR, User engagement	Self-collected
Wu et al. (2017)	Value reinforcement	User engagement	Self-collected
Zheng et al. (2018)	Value reinforcement	CTR	Self-collected
Zihayat, Ayanso, Zhao, Davoudi, and An (2019)	Value ranking	User engagement	Self-collected
Zou et al. (2019)	Value reinforcement	CTR, User engagement	Self-collected
Lu et al. (2020)	Value ranking	User engagement	Self-collected
Spyridou, Djouvas, and Milioni (2022)	Value ranking	CTR, User engagement	Self-collected

Table 5
Media value-aware recommender systems.

Reference	Technique used	Optimised value	Dataset
Iwata, Saito, and Yamada (2006)	Value objective	Sales and revenue	Self-collected
Iwata, Saito, and Yamada (2008)	Value objective	Sales and revenue	Self-collected
Park and Tuzhilin (2008)	Value objective	Distribution	MovieLens
Azaria et al. (2013)	Value ranking	Sales and revenue	Self-collected
Park (2013)	Value objective	Distribution	MovieLens, Book-Crossing
Ho et al. (2014)	Value objective	Distribution	MovieLens
Vargas and Castells (2014)	Value objective	Distribution	Netflix Prize, Million Song
Wang, Gong, Li, and Yang (2016)	Value ranking	Distribution	MovieLens, Netflix Prize, Jester
Antikacioglu and Ravi (2017)	Value ranking	Distribution	MovieLens, Netflix Prize
Hamedani and Kaedi (2019)	Value ranking	Distribution	MovieLens, Netflix Prize
Najafabadi et al. (2021)	Value policy	Sales and revenue	Self-collected
Zhang, Ferreira, Godinho de Matos, and Belo (2021)	Value policy	Sales and revenue	Self-collected

Conventional news recommendation strategies

The reputation of a news company is directly related to the impact of the information it provides on society (i.e., breaking news) (Zhou, Calder, Malthouse, & Hessary, 2021). The business model may be subscription based, advertising based, or both. Conventionally, the number of clicks or views a given news item obtains during its overall lifespan is directly related to the organization's returns. As a result, traditionally, companies whose core business is sharing information in the form of news may be interested in generating higher profits by optimizing user interaction. Since the click-through rate (CTR) is directly related to an organization's revenue, a common goal is to maximise the number of clicks. Therefore, traditional news RSs (Feng, Khan, Rahman, & Ahmad, 2020; Karimi, Jannach, & Jugovac, 2018) use CTR as a primary indicator to feed probabilistic techniques to determine which articles most closely match the reader's interests. The systems generate news candidates with the highest probability of being clicked by the users.

On the CTR-engagement relationship

As for advertising, although the CTR measures the probability of clicks in the current step, it does not capture the engagement that may occur due to the action itself. In fact, even if a user clicks on an article simply for curiosity, he or she might not necessarily be interested in reading it. Consequently, a growing body of work (Besbes et al., 2016; Lu et al., 2020; Zihayat et al., 2019) has considered the relationship between CTR and user engagement by proposing to optimise the latter. Besbes et al. (2016) formulated a heuristic methodology that examines the probability of clicking on a news item and the engagement effect that it triggers. Specifically, they express the relationship between click (the likelihood of clicking on an article when recommended) and engagement (the probability of clicking on an article when it hosts a recommendation). Through this formulation, the news is proposed also considering the future navigation paths of the contents. Instead, Zihayat et al. (2019) proposed a probabilistic methodology that simultaneously considers an article's recentness and user–article interaction (i.e., dwell time) to recommend news based on user utility criteria. Moreover, as observed by Lu et al. (2020) and Spyridou et al. (2022), news recommendation differs from many traditional recommendation domains, such as e-commerce or entertainment, in that news organizations have a clear responsibility to society to provide high-quality information. Algorithms should first and foremost consider the civic role of journalism for an informed citizenry and optimise the editorial value of news (i.e., a mix of serendipity, dynamism, diversity, and coverage) rather than looking solely at CTR.

Optimizing long-term metrics

As with other value-aware systems, the relationship between value and time should not be underestimated. In some cases optimizing exclusively for short-term CTR may prove counterproductive if the news provided is not of interest for the user. Taking this into consideration, several works (Li et al., 2010; Wu et al., 2017; Zheng et al., 2018; Zou et al., 2019) have proposed methodologies to optimise long-term metrics. For example, Wu et al. (2017) propose optimizing long-term user engagement by maximizing the total number of clicks per period using a multi-armed bandit system. The model also considers that, in some cases, the user may abandon the system due to incorrect recommendations. A similar approach based on contextual bandits was originally proposed by Li et al. (2010) to maximise the total number of user clicks. More advanced approaches based on reinforcement learning have been proposed by Zheng et al. (2018) and Zou et al. (2019) to optimize both CTR and long-term user engagement while considering the user's return pattern on the platform in addition to click information.

4.2.4. *Media recommendation*

Some value-aware recommender systems have been designed to optimise the value of multimedia services. Below, we provide an overview of the main topics in the literature concerning the optimization of user engagement, the effects on the distribution of items with which the user interacts, and the resulting increase in sales.

Table 5 summarises the literature on value-aware media recommendation systems.

On the effects of optimizing user engagement on item distribution

In contrast to ordinary goods (e.g., physical products), movies, music and other digital goods are referred to as information goods because their production and distribution costs are negligible and they can be copied, shared, rented or resold easily (Najafabadi et al., 2021). As with news systems, the main business models of companies providing multimedia services are based on either subscriptions or advertising.

Table 6
Datasets used in VARS literature.

Dataset	Domain	Content	Availability
FoodMart (Corporation, 1998)	Product	Contains transaction data, product metadata and customer demographics of a supermarket chain	https://github.com/julianhyde/foodmart-data-hsqldb
Amazon review (Ni, Li, & McAuley, 2019)	Product	Contains product review data and metadata crawled from Amazon e-commerce site	https://nijianmo.github.io/amazon/index.html
JD (Gu et al., 2020)	Product	Contains data collected from the recommender systems logs of the JD Chinese e-commerce site	https://github.com/guyulongcs/CIKM2020_DMT
Dunnhumby (Ventatesan, 2007)	Product	Contains transaction data from a subset of households that make frequent purchases from a retailer	https://www.dunnhumby.com/sourcefiles
SPMF/Retail (Fournier-Viger et al., 2016)	Product	Contains customer transaction data from a Belgian retail store	https://www.philippe-fournier-viger.com/spmf/index.php?link=datasets.php
ChainStore (Pisharath, 2005)	Product	Contains transaction data and product metadata from a supermarket chain in California	http://cucis.ece.northwestern.edu/projects/DMS/MineBench.html
EC-REC (Lin et al., 2019)	Product	Contains records of impressions, clicks and purchases from a large-scale e-commerce platform	https://drive.google.com/open?id=1rbidQksa_mLQz-V1d2X43WuUQQVa7P8H
REC-RL (Pei et al., 2019)	Product	Contains user interaction data collected from a real-world e-commerce platform	https://github.com/rec-agent/rec-rl
Epinions (Richardson & Domingos, 2002)	Product	Contains who-trust-whom online social network data from the Epinions consumer review site	https://snap.stanford.edu/data/soc-Epinions1.html
MovieLens (Harper & Konstan, 2016)	Media	Contains movie ratings collected over various time periods from the MovieLens web site	https://grouplens.org/datasets/movielens/
Netflix Prize (Bennett, Lanning, et al., 2007)	Media	Contains anonymous movie ratings from subscribers to the Netflix online movie rental service	https://www.kaggle.com/datasets/netflix-inc/netflix-prize-data
Book-Crossing (Ziegler, McNee, Konstan, & Lausen, 2005)	Media	Contains anonymised data of implicit/explicit book ratings from the Book-Crossing community	http://www2.informatik.uni-freiburg.de/~cziegler/BX/
Million Song (McFee, Bertin-Mahieux, Ellis, & Lanckriet, 2012)	Media	Contains audio features and metadata for over a million contemporary popular music tracks	http://millionsongdataset.com/
Jester (Goldberg, Roeder, Gupta, & Perkins, 2001)	Media	Contains anonymous ratings of jokes by users of the Jester Joke Recommender System	https://eigentaste.berkeley.edu/dataset/

Thus, especially for companies in the entertainment industry, user engagement is directly related to profits; as a result, RSs are traditionally designed with the goal of providing the user with the content of greatest interest (Gomez-Uribe & Hunt, 2015).

However, given the considerably large amount of content available, RSs tend to recommend the most popular items, risking boring the users with poorly tailored recommendations (Fleder & Hosanagar, 2009; Lee & Hosanagar, 2014, 2019). To keep users engaged, one of the main techniques is to optimise the distribution of recommended items (recall effects on distribution are part of the value taxonomy in Section 2.2.2) with the goal of helping the user discover surprisingly new and relevant items. This can be done, for example, by increasing the diversity (Kunaver & Požrl, 2017) of recommendations (Antikacioglu & Ravi, 2017; Hamedani & Kaedi, 2019; Vargas & Castells, 2014) or promoting long-tail items (Ho et al., 2014; Park, 2013; Park & Tuzhilin, 2008) that tend to be proposed less by RSs because of popularity bias.

Optimizing sales revenue according to the business model

In addition to user engagement, research on media value-aware recommenders have proposed approaches to optimise other value indicators. Some works (Azaria et al., 2013; Iwata et al., 2006, 2008) have proposed domain-specific approaches to recommend films that have the highest probability of maximizing system sales revenue. Azaria et al. and Iwata et al. proposed two different variants of their approach depending on whether the customer pays a subscription (*subscription-based business model*) to have the opportunity to watch several movies in a given time frame (Azaria et al., 2013; Iwata et al., 2006) or a fixed price (*on-demand business model*) for individual movies (Azaria et al., 2013; Iwata et al., 2008).

The importance of the value-aware approach on the overall revenues of a movie provider based on an on-demand business model has also been studied in detail in two recent papers (Najafabadi et al., 2021; Zhang et al., 2021). In particular, according to Zhang et al. (2021), recommendation systems that aim solely at profit optimization could produce negative effects on customer surplus (i.e., price paid by the customer minus willingness to pay) and risk driving customers away from the company. Instead, according to Najafabadi et al. (2021), personalizing pricing would allow the offer to be more tailored to the customer's willingness to pay and simultaneously create more profit for the sellers and surplus for the customers.

4.3. Datasets

In many studies, VARS have been trained and evaluated on public datasets. Unlike traditional datasets, the majority of the latter contain economic value information. Below, we present the main datasets used in the literature.

As shown in Table 6, most datasets are used to design product or media value-aware recommender systems. Some studies that proposed product VARS (Chen et al., 2008; Mu-Chen Chen et al., 2007; Yang et al., 2017) have exploited the FoodMart dataset (Corporation, 1998). This is a Microsoft SQL Server 2000 sample database of a supermarket. The dataset contains 5581 customers, 1559 products, and 20,522 purchase transactions. In addition, master data about customers (e.g., country) and products (e.g., brand) are presented together with sales data (e.g., price, cost, profitability). Other studies on product VARS (Cai & Zhu, 2019; He et al., 2022; Li & Lakshmanan, 2014; Yang et al., 2017) have exploited different datasets crawled from Amazon (McAuley, Pandey, & Leskovec, 2015; Ni et al., 2019) and

Epinions (Richardson & Domingos, 2002). These datasets are primarily based on product review data from various product categories and contain customer ratings, text reviews, and product metadata (e.g., brand, category, price). Furthermore, other works (Ju, 2017; Ma et al., 2019; Yang et al., 2017) have leveraged supermarket transaction datasets such as Dunnhumby (Ventatesan, 2007), SPMF/Retail (Fournier-Viger et al., 2016), and Chainstore (Pisharath, 2005), which contain customer, product, and purchase transaction information. Finally, other works (Gu et al., 2020; Lin et al., 2019; Nguyen et al., 2017; Pei et al., 2019; Zou et al., 2019) used e-commerce datasets such as EC-REC (Lin et al., 2019), REC-RL (Pei et al., 2019) and JD (Gu et al., 2020) that, together with customer, product, and pricing information, contain user–item interaction data (e.g., click, add-to-cart).

Other studies that investigated media VARS (Antikacioglu & Ravi, 2017; Hamedani & Kaedi, 2019; Han et al., 2019; He et al., 2022; Ho et al., 2014; Hosein et al., 2019; Jannach & Adomavicius, 2017; Park, 2013; Park & Tuzhilin, 2008; Wang et al., 2016) relied on the well-known MovieLens dataset (Harper & Konstan, 2016). This is a very popular dataset that is used extensively in research on RSs. The dataset exists in several versions and contains movie rating data from the homonymous website. The largest version is MovieLens 25 M which contains 162,000 users, 62,000 movies, and 25 million ratings. Unlike the previous datasets, MovieLens does not explicitly contain product pricing data. Therefore, in several studies (Han et al., 2019; He et al., 2022; Hosein et al., 2019; Jannach & Adomavicius, 2017), some methodologies based on probability calculations have been proposed to add this information to design VARS. Furthermore, other studies (Antikacioglu & Ravi, 2017; Hamedani & Kaedi, 2019; Ho et al., 2014; Park, 2013; Park & Tuzhilin, 2008; Wang et al., 2016) have used the dataset to design algorithms capable of optimizing product distributions without the need to add pricing information. Different research works on media VARS (Antikacioglu & Ravi, 2017; Hamedani & Kaedi, 2019; Park, 2013; Park & Tuzhilin, 2008; Vargas & Castells, 2014; Wang et al., 2016) have adopted a similar philosophy and are based on famous datasets that do not contain pricing information, such as Netflix Prize (Bennett et al., 2007), Book-Crossing (Ziegler et al., 2005), Million Song (McFee et al., 2012), and Jester (Goldberg et al., 2001).

5. Discussion

Value-aware recommendation systems offer many business benefits over traditional systems. However, optimizing value brings new challenges. In this section, we discuss some of these challenges to guide future research directions.

5.1. Balancing accuracy and profitability

Early studies in the literature (Chen et al., 2008; Mu-Chen Chen et al., 2007) focused on optimizing a particular value driver of interest (e.g., CTR, sales, conversion rate). However, although biasing recommendations can in many cases improve some key business indicators, a system that always recommends irrelevant high-profit items could hurt the company's reputation by driving customers away (Jannach & Adomavicius, 2017; Kompan et al., 2021; Zhou & Zou, 2022). To address this issue, many studies (Besbes et al., 2016; Cai & Zhu, 2019; Das et al., 2009; Ghanem et al., 2022; Hosanagar et al., 2008; Li & Lakshmanan, 2014; Long et al., 2018; Louca et al., 2019; Ma et al., 2019; Malthouse et al., 2019; Wang & Wu, 2009; Zhang et al., 2017) propose algorithms to determine the best trade-off between recommendation accuracy and value maximization. In fact, to avoid losing valuable sources of revenue for the organization, the RS must appropriately balance the interests of all key stakeholder groups. Although several studies have addressed this issue, the proposed algorithms are often based on assumptions about a particular type of industry (e.g., retail, entertainment, insurance) (Li et al., 2021; Najafabadi et al., 2021) or business model (e.g., direct sales, subscriptions) (Iwata et al., 2006, 2008), and the methodologies are not always applicable in different contexts. Future research should study this problem in more detail by generalizing methodologies to propose algorithms suitable for each application context. Furthermore, optimizing a certain type of value (e.g., click-through rate) often affects other related indicators (e.g., sales) (He et al., 2022). Studying more in-depth the correlations between the various indicators and their relationships with other business KPIs such as cash flows or inventory levels (Demirezen & Kumar, 2016; Zhang, Dearden, & Yao, 2022), to optimise other types of value for organizations as well (e.g., reducing logistics delays, cost-to-serve or interest rates), could be another interesting research direction for the future.

5.2. On the long-term perspective of value creation

To balance the interests of different parties, many algorithms have been proposed based on constrained optimization techniques. However, these algorithms often perform post-processing operations to optimise short-term performance without considering the long-term effects of recommendations (Ghanem et al., 2022; Hosanagar et al., 2008; Jannach & Adomavicius, 2017). Although widely used in the literature, this approach is risky because if a potential client notices that the recommendations are biased, they may lose trust in the organization and decide to purchase from competitors. To address this issue, reinforcement learning techniques have recently been proposed (Guo et al., 2021; Han et al., 2019; Ji et al., 2021; Ju, 2017; Li et al., 2021; Pei et al., 2019; Theocharous et al., 2015; Wu et al., 2017; Zhao et al., 2020; Zheng et al., 2018; Zou et al., 2019). In this way, the recommendation can be modelled as a sequential decision problem in which an agent interacts with customers to maximise a cumulative reward for the organization. In general, we think that the use of reinforcement learning algorithms to optimise long-term recommendation performance will be highly valued in the next generation of VARS.

5.3. Dynamic pricing for value optimization

Another important point to consider is the variability of certain information (e.g., price) that, together with recommendations, helps influence a customer's decision to purchase from an online service. To date, the literature on VARS has primarily studied how to optimise recommendations while keeping prices stable. Some specialised works (Beladev et al., 2016; Cavenaghi et al., 2022; Jiang & Liu, 2012; Kamishima & Akaho, 2011; Najafabadi et al., 2021; Zhao et al., 2015) have instead proposed further optimizing the sales process by integrating dynamic pricing algorithms into recommendations. In fact, the price of a product is one of the most important purchase drivers for a customer (Cavenaghi et al., 2022; Zhou, Leng, Liu, Cui, & Yu, 2022). Therefore, it is possible to act on this information as well to increase revenue and overall profitability for the organization. The study of the integration of dynamic pricing algorithms in value-aware systems is currently still in its infancy but could be a valuable future research direction.

5.4. Value-aware performance evaluation

To evaluate the performance of VARS (Gunawardana, Shani, & Yogev, 2022; Jannach & Jugovac, 2019; Jannach & Zanker, 2022), some studies (Basu, 2021; Panniello et al., 2016) have performed online A/B tests. Specifically, given the non-deterministic nature of customer purchase choices, randomised controlled field tests are typically considered one of the few reliable performance evaluation methods. However, performing these tests is costly in terms of both time and money on the part of organizations: often, an A/B test can last several months if long-term aspects are to be evaluated and unexpected effects can sometimes occur, for example, due to particular world events that affect the results, making it necessary to rerun the test. In addition, a poorly performing recommendation system could cause significant financial damage to the organization by making performance evaluation very risky. Thus, given the complexity and cost of conducting field tests to evaluate performance, most studies on VARS (Cai & Zhu, 2019; Chen et al., 2008; He et al., 2022; Hosein et al., 2019; Jannach & Adomavicius, 2017; Li & Lakshmanan, 2014; Lin et al., 2019; Ma et al., 2019; Mu-Chen Chen et al., 2007; Nguyen et al., 2017; Pei et al., 2019; Yang et al., 2017; Zhou et al., 2018) exploit offline approaches based on public datasets. However, the most popular public datasets (Bennett et al., 2007; Harper & Konstan, 2016) often do not contain business information (e.g., prices, profits), making it difficult to measure the potential value generated by the recommender. Another important limitation is that it is often unclear under what circumstances the data were sampled. The results obtained by the algorithms could therefore be affected by bias, e.g., due to a particular promotion or certain population characteristics leading to erroneous conclusions. In addition, the results of studies in the literature are often not comparable because the authors measure offline value using ad hoc metrics or simulation systems that attempt to emulate the user's purchase choice. As a result, future research should address this issue to provide more reliable and sustainable performance evaluation methods.

5.5. Trustworthy value-aware recommender systems

Finally, like other AI-based systems, value-aware recommenders should be designed to respect important principles of AI trustworthiness (Kaur, Uslu, Rittichier, & Durresi, 2022), including alignment with human values, robustness and safety, privacy preservation, fairness (Wang et al., 2022), explainability (Vultureanu-Albişi & Bădică, 2022) and transparency, reproducibility, and accountability. Studying each of these aspects in detail could be a profitable research direction. Investigating how to explain VARS recommendations without degrading business value or studying the reproducibility of major algorithms in the literature could provide interesting hints for future contributions.

6. Conclusion

In this work, we provide a systematic review of recent advances in value-aware recommender systems. These systems are designed to be integrated into commercial applications to optimise the economic value of recommendations. Value-aware recommender systems could be used, for example, in e-commerce to optimise profitability, in advertising platforms to increase customer lifetime value, and in online news services to maximise user engagement. The main algorithms in the value-aware literature are based on post-processing methodologies, integration of objective functions of known recommendation algorithms, or reinforcement learning techniques. However, with the understanding of the key benefits of these systems comes the challenge of appropriately balancing the interests of consumers, producers, and organizations while maintaining high recommendation performance in the short and long term. More in-depth research is required to design higher-performing systems following recent trustworthy AI principles, effectively manage pricing information to optimise value and improve offline and online performance evaluation methodologies.

CRediT authorship contribution statement

Alvise De Biasio: Conceptualization, Methodology, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Andrea Montagna:** Conceptualization, Methodology, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Fabio Aiolli:** Conceptualization, Resources, Writing – review & editing, Supervision. **Nicolò Navarin:** Conceptualization, Methodology, Resources, Writing – review & editing, Supervision, Project administration.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

Acknowledgment

This work was partially funded by estilos srl.

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