



# Economic recommender systems – a systematic review

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## ABSTRACT

Many of today's online services provide personalized recommendations to their users. Such recommendations are typically designed to serve certain user needs, e.g., to quickly find relevant content in situations of information overload. Correspondingly, the academic literature in the field largely focuses on the value of recommender systems for the end user. In this context, one underlying assumption is that the improved service that is achieved through the recommendations will in turn positively impact the organization's goals, e.g., in the form of higher customer retention or loyalty. However, in reality, recommender systems can be used to target organizational economic goals *more directly* by incorporating monetary considerations such as price awareness and profitability aspects into the underlying recommendation models. In this work, we survey the existing literature on what we call *Economic Recommender Systems* based on a systematic review approach that helped us identify 135 relevant papers. We first categorize existing works along different dimensions and then review the most important technical approaches from the literature. Furthermore, we discuss common methodologies to evaluate such systems and finally outline the limitations of today's research and future directions.

## 1. Introduction

*Recommender Systems (RSs)* (Jannach et al., 2010) have become an integral part of many modern online services, for example, on Amazon, Netflix, YouTube, or Spotify. Typically, the recommendations provided by the system are designed to serve certain user needs. On the mentioned e-commerce and media streaming sites, for example, these systems support users in navigating large information spaces, thereby helping them discover relevant content that they were previously not aware of.

The academic literature on RSs has traditionally focused on the different types of value that such systems create for *users*, in particular by proposing increasingly sophisticated machine learning models to predict which items are relevant for them in a given situation. An underlying assumption of this user-centric perspective is that by creating value for consumers through personalized recommendations, providers expect certain benefits for the organization as well, for example, through increased customer engagement, loyalty, and retention (Domingues et al., 2013; Garcin et al., 2014; Holtz et al., 2020; Gomez-Urbe and Hunt, 2016).

Only during the last few years, researchers increasingly emphasize the fact that in practical applications of RSs, the interests of multiple stakeholders have to be *explicitly* taken into account. Correspondingly, the underlying systems have to be designed to create value both for

consumers, recommendation providers, and maybe even further stakeholders (Abdollahpouri et al., 2020; Jannach and Adomavicius, 2016; Jannach and Zanker, 2022).

In practice, the business value an RS creates for providers is measured through various *key performance indicators (KPIs)*, see De Biasio et al. (2023b) and Jannach and Jugovac (2019). Besides the mentioned indirect effects of recommendations on customer engagement and retention, organizations rely on various forms of conversion rates to gauge the effectiveness of a system. In many cases, firms directly assess the impact of recommendations by analyzing the effects on sales numbers (Pathak et al., 2010; Garfinkel et al., 2007; Panniello et al., 2016a). In particular, the use of side or contextual information (Sun et al., 2019; Villegas et al., 2018) has proven useful in many circumstances to improve business KPIs (Panniello et al., 2016a; Cooke et al., 2002; Gorgoglione et al., 2011; Panniello and Gorgoglione, 2012; Panniello et al., 2014, 2009b,a; Gorgoglione and Panniello, 2009).

Therefore, it becomes desirable for companies to incorporate relevant knowledge into the underlying algorithms so that the resulting recommendations can drive these KPIs more directly in the desired direction (Panniello et al., 2016a; Cooke et al., 2002; Gorgoglione et al., 2011). One important domain-independent approach in this context is to consider purchase-related information in the recommendation

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models, in particular regarding the profit that results from individual purchase transactions, see Jannach and Adomavicius (2017). Moreover, such algorithms may implement several other theories and mechanisms from the economics and marketing literature, considering, for example, the role of promotions and discounts, price sensitivity, or consumer utility.

These approaches, which we call *Economic Recommender Systems* (ECRSs), are highly relevant in practice. Unfortunately, the literature on this topic is largely scattered. With this paper, we provide a systematic review of the field, which should serve researchers and practitioners alike as a starting point to understand the state-of-the-art in the area. Our systematic literature search surfaced more than one hundred relevant papers, which we categorize into five main dimensions of analysis, see Section 3. In the main part of the survey, Section 4, we then discuss existing ECRSs technical approaches. Afterward, we analyze existing methodologies to evaluate such systems in Section 5. Finally, we discuss open challenges and future research directions in the field in Section 6. The paper ends by highlighting some managerial implications of using ECRSs in real-world environments.

## 2. Background and related work

In this section, we first provide more background on the business value of recommendations. We then characterize the concept of ECRSs in more depth. Finally we discuss the relationships of ECRSs to neighboring topics in RSs research.

### 2.1. Business value of recommender systems

RSs, as mentioned above, are often designed to serve both user (Senecal and Nantel, 2004; Bollen et al., 2010; Chen et al., 2004; Hinz and Eckert, 2010; Häubl and Trifts, 2000) and organizational purposes (Jannach and Adomavicius, 2016; van Capelleveen et al., 2019; Gorgoglione et al., 2019; Maslowska et al., 2022). Regarding the organizational purposes, there are various ways in which an RS can generate value for a business (Adomavicius and Tuzhilin, 2005; Amatriain and Basilico, 2016; Gomez-Urbe and Hunt, 2016; Amatriain, 2013; Schafer et al., 1999, 2001; Xiao and Benbasat, 2007; Belluf et al., 2012; Panniello, 2014), considering economics and marketing aspects (Hwang and Li, 2014; Hanafizadeh et al., 2021; Oechslein, 2014; Krasnodebski and Dines, 2016; Ren and Zhang, 2021), e.g., by converting website visitors into buyers, increasing cross-selling opportunities or building customer loyalty (Schafer et al., 2001).

In the literature, a number of general categories were identified to characterize how RSs may create business value and how the business value can be measured (De Biasio et al., 2023b; Jannach and Jugovac, 2019). The typical measures and corresponding KPIs include (Jannach and Jugovac, 2019):

- The number of *clicks* from recommendations, often measured by the *click-through rate* (CTR);
- The degree of *user adoption* of the system, often measured by the *conversion rate* (CVR);
- The overall *revenue* generated from the *sales* of the firm's products and services;
- The possible effects on the *sales distribution* of the items sold, e.g., shifting toward more profitable items;
- The overall degree of *user engagement* with the platform, as indicator of *customer satisfaction*.

RSs that are designed to optimize one or more of the above business values are generically referred to in the literature as “value-aware” (De Biasio et al., 2023b). Depending on the business industry (e.g., retail, entertainment, manufacturing) or the revenue model (e.g., transaction-based, advertising, subscription) (Resnick and Varian, 1997; Rabanser and Ricci, 2005; Herder, 2019; Mehrotra and Carterette, 2019; Li et al., 2018; Chen et al., 2009; Hoffman and Novak, 2005) the company

may want to optimize certain business values rather than others. For example, in the case where the revenue model is primarily transaction-based (e.g., Walmart), since there is a direct link between purchases and revenue, the company might be interested in shifting the customer behavior towards the purchase of the more profitable items (Panniello et al., 2016b). In contrast, in case the organization's revenue model is based on ads (e.g., YouTube), the company may be interested in increasing the number of clicks (Davidson et al., 2010) as this is directly related to the consumption of ads that providers pay to see their brand advertised. Finally, a company might also be interested in optimizing user engagement (Gomez-Urbe and Hunt, 2016) in the case of subscription-based models (e.g., Netflix) as this positively correlates with retention.

### 2.2. Economic recommender systems

While there are various ways in which a value-aware RS can create value for users and providers, and while there are several KPIs that firms might seek to optimize, ultimately, the provision of a recommendation service almost always serves some economic goal of the organization such as profit and growth. However, we note that some forms of value creation are more directly targeting profitability aspects than others. An increase in revenue through recommendations or a shift in the sales distribution toward the most lucrative items is almost directly reflected in a profit improvement (Hosanagar, 2008; Chen et al., 2008; Pei et al., 2019). On the other hand, a growth in user engagement, as in the case of Netflix (Gomez-Urbe and Hunt, 2016), with more customers joining and fewer leaving, is sometimes only indirectly reflected in higher long-term profits for the organization.

In this survey, we focus on the first type of the described recommendation approaches, i.e., a particularly prominent subset of value-aware RSs (De Biasio et al., 2023b) that target economic effects in a more direct way. Typical examples in this context are: RSs that consider company profit and customer relevance in a balanced way (Nemati and Khademolhosseini, 2020; Concha-Carrasco et al., 2023; Cai and Zhu, 2019; Chen et al., 2008; Kompan et al., 2022); systems that leverage discounts and pricing algorithms to trigger purchases (Jiang and Liu, 2012; Adelnia Najafabadi et al., 2022; Zhao et al., 2015; Jannach and Ludewig, 2017; Jiang et al., 2015); or methods that consider customers' price sensitivity to recommend items more in line with their price preferences (Ge et al., 2014; Chen et al., 2017; Zheng et al., 2020, 2021; Zhang et al., 2022b). We call such systems economic recommender systems, and we informally characterize them as follows:

*An Economic Recommender System (ECRS) is an RS that exploits price and profit information and related concepts from marketing and economics to directly optimize an organization's profitability.*

Later in this work (Section 3), we identify five key approaches from the literature to build ECRSs, which we divide into customer and organization-oriented ones, depending on the focus of the underlying algorithms. Customer-oriented approaches in the literature, for instance, integrate purchasing behavior mechanisms (e.g., price sensitivity) into the models to generate more relevant recommendations that will automatically lead to more profit. Organization-oriented ones, on the other hand, apply particular organizational strategies (e.g., profit awareness, promotional pricing) to optimize profit.

Since most RSs may at least indirectly target some profit-related or growth-related goal, the boundaries between an economic RS and a “traditional” one may sometimes appear blurry. However, a clear distinction can often be made depending on the underlying revenue model (Chen et al., 2009; Resnick and Varian, 1997; Hoffman and Novak, 2005). For example, click-through rate maximization may be seen as an indirect method for profit optimization in case it is only about increasing site interactions (Guo et al., 2021; Wu et al., 2017). However, it may also be considered as an ECRS method in case there

is some revenue associated with each click event (e.g., commissions suppliers pay to marketplaces for each generated impression), as in the case of an advertising revenue model (Malthouse et al., 2019b; Theocharous et al., 2015; Zhang et al., 2017b).

Concluding our characterization of ECRSs, it is important to note that considering certain types of economic information to an inappropriate extent may also lead to *unintended negative effects* and *behavioral harms* of recommendations (Adomavicius et al., 2022; Hazrati, 2021; Dorner et al., 2013). Specifically, it is vital to ensure that an ECRS does not negatively impact the user's trust (Liao et al., 2022) in the organization (Hosanagar, 2008; Ghanem et al., 2022; Panniello et al., 2016b; Basu, 2021; Panniello et al., 2016a). Indeed, trust is one of the most important factors driving adoption (Benbasat and Wang, 2005; Komiak, 2006) and purchase intention (Nilashi et al., 2016; Patnaik and Patnaik, 2022). Recommendations that are irrelevant (Chau et al., 2013; Wang et al., 2015; Zhang et al., 2013; Nguyen and Hsu, 2022), manipulative (Köcher et al., 2019; Adomavicius et al., 2013, 2022; Cremonesi et al., 2012; Gretzel and Fesenmaier, 2006; Xiao and Benbasat, 2018; Tsao et al., 2023; De Biasio et al., 2023a), or poorly explainable (Wang et al., 2016; Cramer et al., 2008; Zhang and Curley, 2018) because they are too biased towards the profitable items (Wang and Wang, 2019) can harm trust, leading customers to reactance (Fitzsimons and Lehmann, 2004; Yanping and Yan, 2012) or churning.

Besides trust, there are also other possible harms that may emerge in case the recommendation strategy is oriented too strongly toward profit. While algorithms are often designed to improve sales diversity (Kunaver and Požrl, 2017; Adomavicius and Kwon, 2012) or to stimulate the sales or consumption of niche items (Matt et al., 2013; Yi et al., 2022), they in practice might sometimes nudge users to buy the most popular ones (Fleder and Hosanagar, 2007, 2009; Lee and Hosanagar, 2014; Hosanagar et al., 2014; Lee and Hosanagar, 2019; Fleder et al., 2010). Such effects may in turn have profit implications considering that popular items sometimes have lower margins (Garfinkel et al., 2007). Finally, competition effects (Ghoshal et al., 2015; Li et al., 2020a; Zhou et al., 2022) may also be important to consider, since rewarding higher-margin items could push sellers to increase prices (Zhou and Zou, 2021), thus impacting customers' willingness-to-pay (Adomavicius et al., 2018), and market demand (Zhang et al., 2021; Aridor and Gonçalves, 2022).

### 2.3. Related areas in RSs research

ECRSs are related to other important research areas, including the following:

- *Multi-Stakeholder Recommender Systems* (Abdollahpouri et al., 2020; Abdollahpouri and Burke, 2022): where the system is designed to meet the interests of multiple stakeholders (e.g., consumers, providers, suppliers);
- *Multi-Objective Recommender Systems* (Zheng and Wang, 2022; Alhijawi et al., 2023): where the system is designed to optimize several objectives simultaneously (e.g., accuracy, diversity);
- *Fair Recommender Systems* (Deldjoo et al., 2023; Zehlike et al., 2023a,b; Patro et al., 2022; Pitoura et al., 2022): where the system is designed to avoid possible discrimination against certain user or item groups.

The relationships between ECRSs and these other areas can be characterized as follows. Regarding multi-stakeholder RSs, we note that probably any ECRS in practice does not *exclusively* focus on provider profitability but considers the interests of other stakeholders—in e-commerce, in particular, those of consumers or suppliers as well (Cai and Zhu, 2019; Chen et al., 2008). Such multi-stakeholder considerations mean that ECRSs in practice are *multi-objective* RSs that consider different competing objectives, e.g., profitability vs. consumer value (Concha-Carrasco et al., 2023; Ghanem et al., 2022) or short-term vs. long-term profits. However, not every multi-stakeholder RS

necessarily is an economic one, e.g., considering that an RS may also be designed to recommend users to other users (e.g., on dating platforms). Likewise, a multi-objective RS could also optimize non-economic goals, e.g., popularity, which may in turn have a direct inverse relationship with profitability under certain circumstances (Garfinkel et al., 2007). Finally, in terms of fairness, when building an ECRS there is always the possibility that by designing a system too biased (Chen et al., 2023) toward profitable items (Chen et al., 2008, 2007a), the organization might risk being perceived as unfair by consumers. However, there are various other application areas of fair RSs, which are not related to economic aspects or firm profitability, e.g., when the recommender system is designed to avoid discrimination of underrepresented groups in the recommendations.

There are already several surveys on RSs that offer generic introductions (Ko et al., 2022), or focus on certain algorithmic aspects such as deep learning (Zhang et al., 2019; Da'u and Salim, 2020) or context awareness (Sun et al., 2019; Villegas et al., 2018). In addition, various surveys have been published in the above mentioned areas of multi-stakeholder (Abdollahpouri et al., 2020; Abdollahpouri and Burke, 2022) and multi-objective (Zheng and Wang, 2022; Alhijawi et al., 2023) RSs, and on related topics such as fairness (Zehlike et al., 2023a,b; Patro et al., 2022; Pitoura et al., 2022), diversity (Kunaver and Požrl, 2017), trust (Dong et al., 2022), and explainability (Zhang and Chen, 2020; Tintarev and Masthoff, 2007). We refer the readers to these important works for in-depth coverage of the respective topics. The present survey has certain affinities with previous reviews on value-aware (De Biasio et al., 2023b) and price- and profit-aware (Jannach and Adomavicius, 2017) RSs. It however differs from these previous works in various ways. First, our study is the first systematic review of ECRSs based on what in the literature are denoted as PRISMA guidelines (Page et al., 2021), i.e., a systematic article review process, known throughout the literature for its high reliability, which aims to identify all available research relevant to a set of research questions. Moreover, existing value-aware RSs research (De Biasio et al., 2023b) investigated how to generically optimize business value through RSs, whereas our research on ECRSs is focused on direct optimization of profitability. This subset of value-aware RSs is of particular interest to companies because, as we noted in Section 2.2, ultimately, the provision of a recommendation service almost always serves some economic goal of the organization such as profit and growth. In addition, the present research on ECRSs also embraces customer-oriented approaches (e.g., price-sensitive recommendations) that had not been studied by previous research on value-aware RSs. Furthermore, previous work on price- and profit-aware RSs (Jannach and Adomavicius, 2017) also focused on profitability optimization. However, this earlier research did not cover a number of important approaches that were identified in this survey (e.g., economic utility modeling methods). Finally, our present review also discusses methodological questions (e.g., performance evaluation methods) that were not addressed in previous works.

### 3. Methodology

The present study follows a systematic review process based on *Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA)* (Page et al., 2021) guidelines. The PRISMA article selection process is recognized throughout the scientific community as a rigorous and reliable methodology. The process aims to identify, evaluate, and interpret all available research relevant to a particular research question, topic area, or phenomenon of interest while ensuring high reproducibility of results. In the following, we report: the dimensions of analysis considered in the study, the underlying research questions, the eligibility criteria for article inclusion, the search queries used, the overall article analysis and selection process, and the possible limitations of the survey.



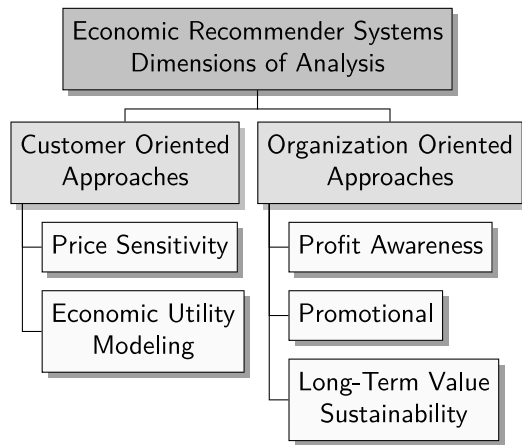


Fig. 1. Economic recommender systems dimensions of analysis.

### 3.1. Decomposing economic recommender systems into different dimensions of analysis

ECRSs can be characterized by several interrelated topics. To identify relevant articles, we therefore followed an inductive process starting from two related surveys (Jannach and Adomavicius, 2017; De Biasio et al., 2023b), decomposing ECRSs into different *dimensions of analysis* (DAs). Specifically, we identified five types of approaches by extending a taxonomy originally presented in a well-known paper in the field, i.e., Jannach and Adomavicius (2017). Four of the DAs that we introduce below, i.e., price sensitivity, profit awareness, promotional and long-term value sustainability, have naturally emerged from the analysis of this article. The fifth dimension, i.e., economic utility modeling, has been identified after a more in-depth analysis of some of the works cited in the article, e.g., Wang and Zhang (2011). In particular, we observed that articles such as the one mentioned here exploited techniques and concepts from the economics literature that are different from those that are used in the articles related to the other DAs. Since we also noticed that recently various other articles that exploited similar techniques were published, we decided to group them into a separate DA. As we will also report later in more detail in Section 4, given that we identified a substantial number of works for each DA, we are confident that our categorization scheme properly reflects the various types of activities in this research area.

As Fig. 1 shows, the five types of approaches can be divided into customer and organization-oriented ones, depending on their main focus. Customer-oriented approaches aim to integrate RSs models with purchasing behavior mechanisms to generate more relevant recommendations that could in turn lead to more value for the firm. Instead, organization-oriented ones make use of specific organizational strategies to directly or indirectly optimize business KPIs. Intuitively, the main difference between the two types of approaches is that customer-oriented ones tend to consider the problem from the customer's perspective, while organization-oriented ones tend to consider the problem from the organization's perspective. In particular, customer-oriented approaches are primarily designed to help users find items that are more in line with their needs. As a direct result of pursuing this goal, they also help the company make more profit through an expected increase in sales volume. Instead, organization-oriented approaches are mainly designed to push users toward what help the company improving its business KPIs. Hence, algorithms may not recommend what is best for users, as they are designed to recommend what is best for the company in terms of profitability gains. Below, we explain the rationale behind each approach.

- **DA1: Price Sensitivity** approaches aim to explicitly consider customers' price preferences in the recommendation process. In fact, price is one of the variables that most strongly influence customers' buying behavior (Lichtenstein et al., 1993; Ali and Anwar, 2021). For example, customers are often willing to pay more for certain types of items based on presumed greater utility, better aesthetics, brand prestige, supplier reliability, or a combination of various factors (Jannach and Ludewig, 2017). By considering customers' price sensitivity in the algorithms (Jannach and Adomavicius, 2017), more accurate and relevant recommendations could directly increase the probability of purchase and thus lead to higher sales revenue for the organization.
- **DA2: Economic Utility Modeling** approaches aim to explicitly consider the utility of recommendations for the customer in accordance with an economic perspective. There are many utilitarian dynamics (Scott, 2000) related to the particular type of purchased products (Wang and Zhang, 2011; Ge et al., 2019). For example, if a customer has just purchased a computer or a smartphone, it is very likely that he or she will not purchase the same or a similar product again within a short time. Conversely, there are other products, such as dog food or diapers, for which he or she is very likely to continue buying repeatedly for an extended period of time. Generating more relevant recommendations by considering the customer's utilitarian behavior could increase conversion rates and generate more profits for the firm.
- **DA3: Profit Awareness** approaches aim to directly incorporate profit information into the recommendation models. In fact, profit (i.e., sales revenue minus costs) is one of the most important business KPIs for a successful enterprise (Teece, 1981). Depending on the particular level of this indicator, a company may or may not invest in research and development to grow the business, attract investors to finance its operations, obtain possible financing from banks, and many other issues of strategic interest to entrepreneurs and managers (Geroski et al., 1993). Overall, generating more profitable recommendations by explicitly considering profit information could directly optimize the organization's economic goals.
- **DA4: Promotional** approaches generate recommendations while strategically setting the prices of certain products or focusing the customer's attention on certain brands or promotions. For example, the company can offer certain products at a discounted price (individually or in bundles) to incentivize impulsive buying behaviors (Morgan et al., 2019; Goi, 2009). Similarly, the firm can make customers aware of certain products that they would be unlikely to discover on their own and indirectly trigger a possible purchase in the future (Kotler et al., 1990). Both approaches can be integrated into the recommendation process to optimize profit.
- **DA5: Long-Term Value Sustainability** approaches aim to generate recommendations considering a long-term economic perspective. In fact, long-term sustainable business growth is one of the most important aspects for a company (Lumpkin et al., 2010; Rauch et al., 2005; Ortiz-de Mandojana and Bansal, 2016). For example, a company may be interested in making customers progressively purchase more and more products and services over time to increase their customer lifetime value. Generating recommendations by considering such long-term economic goals of the company thus has the potential to stimulate business growth in a sustainable way over time.

### 3.2. Research questions

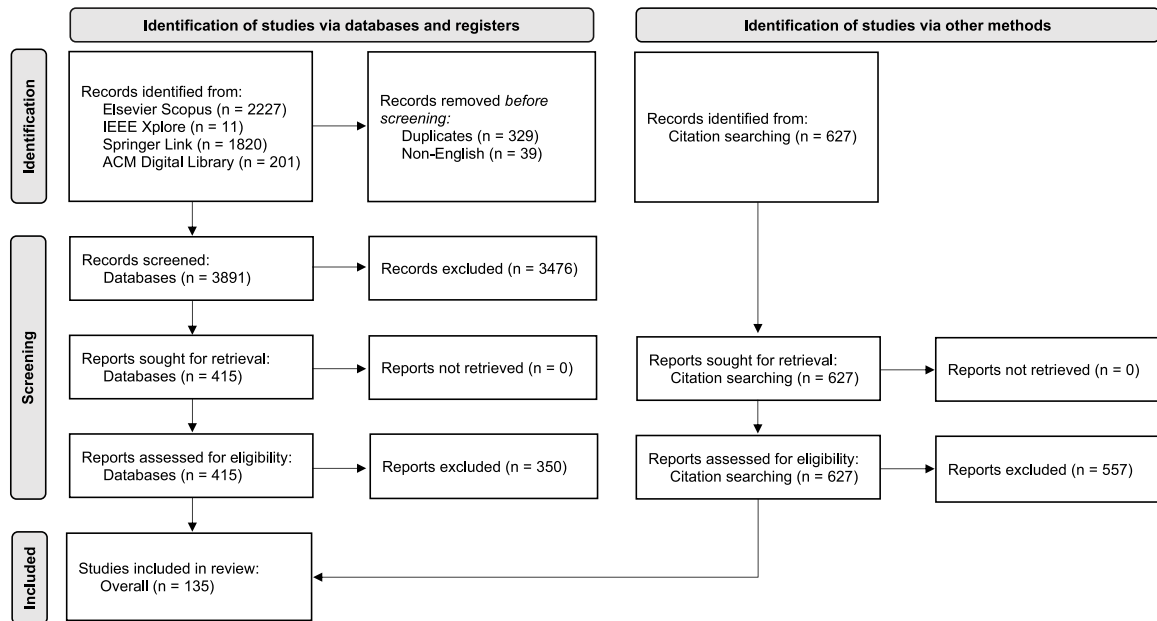
Having identified these DAs, the goal of our work is to review the state-of-the-art of current ECRSs research. More specifically, the present survey aims to answer the following *research questions* (RQs):

- **RQ1:** What technical approaches are used to build ECRSs?

**Table 1**

Search queries and results divided by online database of the different dimensions of analysis on which this article focuses. Queries were run on May 12, 2023 looking for all documents published since January 1, 2000.

ID	Dimension	Search query	Scopus	IEEE	Springer	ACM	Total
DA1	Price sensitivity	((“recommender system”) AND (“price preference” OR “price sensitivity” OR “price elasticity” OR “willingness to pay” OR “price-aware”))	670	2	469	57	1198
DA2	Economic utility modeling	((“recommender system”) AND (“economic”) AND (“utility theory”))	104	0	188	17	309
DA3	Profit awareness	((“recommender system”) AND (“multi-stakeholder” OR “profit-aware” OR “value-aware”))	351	5	290	63	709
DA4	Promotional	((“recommender system”) AND (“dynamic pricing” OR “price personalization” OR “product bundling”))	483	0	423	29	935
DA5	Long-term value sustainability	((“recommender system”) AND (“customer lifetime value” OR “RFM” OR “cumulative profit” OR “long-term value”))	619	4	450	35	1108

**Fig. 2.** PRISMA flow diagram.

- **RQ2:** What evaluation methods are used to assess the performance of an ECRS?
- **RQ3:** What are the main challenges and future research directions in the area of ECRSs?

### 3.3. Search queries

As mandated by the PRISMA guidelines, our survey aims to answer previous RQs by systematically querying online libraries. In particular, taking inspiration from two related systematic review in the RSs field, i.e., [De Biasio et al. \(2023b\)](#) and [Nunes and Jannach \(2017\)](#), we queried Elsevier Scopus, IEEE Xplore, Springer Link, and ACM Digital Library to identify relevant articles. Those online databases are known throughout the literature to contain all the major research works in computer science. For each of these databases, we created a *search query* for the previous DAs by analyzing the most recurring key terms identified in a series of specialized articles extracted from the literature of two related surveys ([Jannach and Adomavicius, 2017](#); [De Biasio et al., 2023b](#)). In [Table 1](#), we report the used search queries and the number of identified documents.

### 3.4. Eligibility criteria

To be included in the review, articles must pass a rigorous analysis process. Specifically, articles must meet the following *eligibility criteria* (EC):

- **EC1:** Articles must focus on research questions related to one of the dimension of analysis of ECRSs.
- **EC2:** Articles must explicitly mention the business KPIs included in the search queries.
- **EC3:** Articles must be unique, written in English, and the full content must be accessible to the authors.
- **EC4:** Articles must be peer-reviewed by either scientific journals or conferences.
- **EC5:** Graduate theses and doctoral dissertations are not included.

### 3.5. Article selection process

As shown in the PRISMA flow diagram in [Fig. 2](#), we followed a multi-stage process to identify all the relevant resources included in this review. In the first identification phase 2227 articles from Elsevier Scopus, 11 articles from IEEE Xplore, 1820 articles from Springer Link, and 201 articles from ACM Digital Library were identified for subsequent analyses. In this phase, 329 duplicated records and 39 non-English articles were identified and removed. In the second screening phase, the titles and abstracts of the remaining 3891 articles were analyzed, and 3476 records were removed because the covered topics were not relevant to the present review. In this phase, 415 articles were then sought for retrieval and assessed for eligibility, excluding 350 articles after full text reading. From this subset of 65 eligible articles, an additional 627 articles were identified by searching for references in

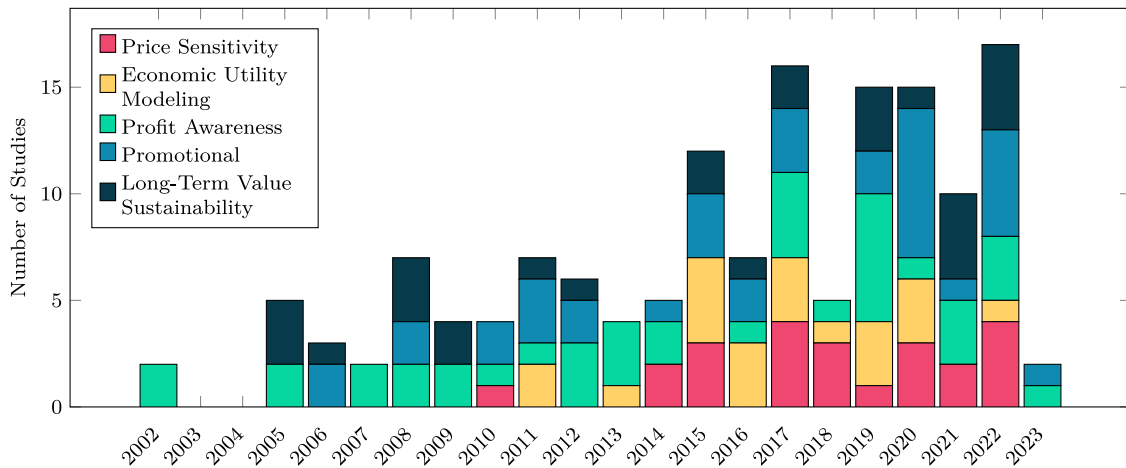


Fig. 3. Distribution of surveyed papers per year divided by dimension of analysis.

Table 2

Top-10 conferences and journals ranked by number of published articles from the surveyed literature.

Top-10 conferences	#Ref.	Top-10 journals	#Ref.
ACM Conference on Recommender Systems (RecSys)	11	Expert Systems with Applications	4
ACM Conference on Research and Development in Information Retrieval (SIGIR)	7	IEEE Transactions on Knowledge and Data Engineering	4
International Conference on World Wide Web (WWW)	7	Decision Support Systems	4
ACM International Conference on Knowledge Discovery and Data Mining (SIGKDD)	7	Electronic Commerce Research and Applications	2
ACM Conference on Information & Knowledge Management (CIKM)	6	Knowledge-Based Systems	2
International Conference on Data Mining (ICDM)	4	ACM Transactions on Information Systems	2
ACM Conference on Web Search and Data Mining (WSDM)	2	Information Sciences	2
IEEE Conference on Data Engineering (ICDE)	2	Electronic Markets	1
International Conference on Information Systems (ICIS)	2	Future Generation Computer Systems	1
European Conference on Information Systems (ECIS)	2	IEEE Intelligent Systems	1

their bibliographies. These articles were then assessed for eligibility, removing 557 records after reading the full text. At the end of this overall process, 135 studies were included in the review. Of these 135 articles included in the review, 58.52% were published in international conferences, 38.52% in scientific journals and the remaining 3.01% in book chapters. As can be seen from Table 2, where we report the top-10 conferences and journals by number of published articles, many researchers published their work in well-known venues in the field of computer science and particularly in the realm of recommender systems. In Fig. 3, we show some statistics of the references obtained at the end of the analysis process by reporting the distribution by year of surveyed papers divided by DA. As can be seen from the figure, there is a growing interest in the literature for all ECRSs dimensions.

### 3.6. Study limitations

The possible study limitations (SL) are the following:

- **SL1:** Articles were primarily selected from Elsevier Scopus, IEEE Xplore, Springer Link, ACM Digital Library, and from reference searches in the bibliographies of articles that passed the screening stage. Additional online libraries may be considered in future research.
- **SL2:** The study does not cover preprints, non-English articles, non-accessible articles, graduate theses, doctoral dissertations, industry products, and demos.
- **SL3:** Other dimensions of analysis of ECRSs beyond those identified in Section 3.1 are left for possible future extensions of this work.
- **SL4:** The study focuses mainly on algorithmic aspects of ECRSs and leaves the in-depth analysis of their managerial implications for the future.

- **SL5:** Although the PRISMA review process can be considered very reliable overall, there is still a small degree of discretionality in the definition of research questions, the selection of keywords to be included in search queries, and the application of eligibility criteria.

## 4. Technical approaches

In this section, we discuss<sup>1</sup> the underlying algorithmic approaches to each of the ECRSs dimensions of analysis introduced in Section 3.1, i.e., price sensitivity, profit awareness, promotional, long-term value sustainability, and economic utility modeling.

In Table 3 we report the studies identified by the present survey that propose technical approaches, categorized by DA and algorithmic method. The approaches can be divided into in- and post-processing<sup>2</sup> methods, depending on the time the economic value optimization occurs. In-processing approaches aim to incorporate economic aspects directly into the models, either by extending the objective function of known algorithms (e.g., by introducing new variables or regularizers) or by developing entirely new algorithms. The underlying algorithms

<sup>1</sup> The organization of the discussion of the various algorithmic approaches in the next sections varies from section to section. While this might appear inconsistent at first glance, this organization is a deliberate choice, because we believe that the current organization of the content is more useful for readers to understand the various concepts. For example, in Section 4.2, since the methods presented are based on specific economic theories, we put special emphasis on the underlying utility theories. In contrast, since in Section 4.5 long-term value methods based on reinforcement learning represent a very important part of the literature, we devote a separate section to them.

<sup>2</sup> Pre-processing methods may also exist in industry, e.g., when a recommendation provider wants to rule out certain unprofitable items. Our literature search, however, did not surface such approaches.

**Table 3**

ECRSs studies divided by dimension of analysis and algorithmic approach.

Approach	Price sensitivity	Economic utility modeling	Profit awareness	Promotional	Long-term value sustainability
In-processing	Umberto (2015), Zhang et al. (2022b), Wu et al. (2022), Maragheh et al. (2022), Zheng et al. (2021), Chen et al. (2021), Zheng et al. (2020), Wang et al. (2020, 2019), Greenstein-Messica and Rokach (2018), Greenstein-Messica et al. (2017), Chen et al. (2017), Sato et al. (2015), Ge et al. (2014) and Chen et al. (2014)	Maragheh et al. (2022), Xu et al. (2020), Wang et al. (2020), Ge et al. (2019), Zhao et al. (2017), Zhang et al. (2017a, 2016), Deng (2015) and Wang and Zhang (2011)	Li et al. (2017), Concha-Carrasco et al. (2023), Dookeram et al. (2022), Nemati and Khademolhosseini (2020), Li et al. (2021), Ma et al. (2019), Lin et al. (2019), Cai and Zhu (2019), Wu et al. (2018), Qu et al. (2014), Huang et al. (2013), Goyal and Lakshmanan (2012), Piton et al. (2011), Akoglu and Faloutsos (2010), Chen et al. (2007b), Wang and Zhou (2005), Brand (2005), Wang et al. (2002b) and Wang et al. (2002a)	Chang et al. (2023), Sun et al. (2022), Avny Brosh et al. (2022), Agarwal et al. (2022), Ghoshal et al. (2021), Wang et al. (2020), Deng et al. (2020), Chang et al. (2020), Kouki et al. (2019), Bai et al. (2019), Liu et al. (2017), Ge et al. (2017), Sato et al. (2015), Massoud and Abo-Rizka (2012), Wu and Teng (2011), Kamishima and Akaho (2011), Kowatsch et al. (2008), Garfinkel et al. (2008) and Garfinkel et al. (2006)	Iwata et al. (2008, 2006), Zhang et al. (2022a), He et al. (2022), Zhan et al. (2021), Ji et al. (2021), Guo et al. (2021), Zhao et al. (2020), Zou et al. (2019), Pei et al. (2019), Wu et al. (2017), Ju et al. (2017) and Theocharous et al. (2015)
Post-processing	Kompan et al. (2022), Cavenaghi et al. (2022), Wadhwa et al. (2020), Shiu et al. (2018), Guo et al. (2018), Yang et al. (2017), Jannach and Ludewig (2017) and Backhaus et al. (2010a)	Dai et al. (2020), Zheng (2019), Ren et al. (2019), Zheng and Pu (2018), Yang et al. (2017), Zhao et al. (2015) and Adamopoulos and Tuzhilin (2015b)	Ghanem et al. (2022), Seymen et al. (2022), Kompan et al. (2022), Ren and Zhang (2021), Huang et al. (2021), Malthouse et al. (2019b,a), Louca et al. (2019), Zhang et al. (2017b), Yang et al. (2017), Azaria et al. (2013), Wang and Wu (2012, 2009), Das et al. (2009), Chen et al. (2008, 2007a) and Lu et al. (2014)	Seymen et al. (2022), Adelnia Najafabadi et al. (2022), Kini and Manjunatha (2020), Guo et al. (2020), Ettl et al. (2020), Jannach and Ludewig (2017), Demirezen and Kumar (2016), Beladev et al. (2016), Zhao et al. (2015), Jiang et al. (2015), Zhu et al. (2014), Jiang and Liu (2012), Jiang et al. (2011), Backhaus et al. (2010a) and Backhaus et al. (2010b)	Hosein et al. (2019), Hosanagar (2008), Panniello et al. (2016b) and Basu (2021)

may be based, for example, on supervised or reinforcement learning paradigms. Post-processing approaches, on the other hand, can be mounted on top of any recommender and aim to transform the recommendations generated from the baselines by applying specific heuristic economic criteria. These may incorporate economic value by simply re-ranking the output of the original algorithm or by exploiting additional models.

Analyzing the distribution of the studies in Table 3, we can make some observations. In particular, it can be noted that there are several relevant works for all the DAs. In addition, in-processing and post-processing methods are equally used across all dimensions. This implies that the research field is broad and that there are various important lines of active research. Overall, given that there is a substantial number of works in each DA, we are confident that our categorization scheme properly reflects the various types of activities in this research area.

**Notation.** In the following, we introduce the main notation used in the paper, see Table 4. Formally, the vast majority of the approaches we discuss in this survey refer to the *top-k recommendation problem* (Rendle, 2022), i.e., the problem of determining the best  $k$  items to recommend to each user. All algorithms designed to address this particular problem consider a set  $\mathcal{U} = \{u_1, \dots, u_m\}$  of  $m$  users, a set  $\mathcal{I} = \{i_1, \dots, i_n\}$  of  $n$  items, and a user-item interaction matrix  $\mathbf{X}$ , where each entry  $x_{u,i}$  represents the feedback from a user  $u$  towards an item  $i$ . With very few exceptions, the feedback considered is almost always implicit (i.e.,  $x_{u,i} \in \{0, 1\}$ ). This indicates a positive or missing interaction, depending if the user interacted with the item or not (e.g., purchased it). Generally, it is assumed that purchased items are those that are relevant (and maybe satisfactory) for consumers.

Algorithms are often designed (Rendle, 2022) to learn a *scoring function*  $\hat{\mathbf{X}}(\Theta) : \mathbf{X} \rightarrow \{\hat{x}(\Theta) \in \mathbb{R} : 0 \leq \hat{x}(\Theta) \leq 1\}^{m \times n}$  to predict the

**Table 4**

Main notation.

Notation	Definition
$u$	User
$i$	Item
$p_i$	Item's price
$c_i$	Item's cost
$v_i = p_i - c_i$	Item's profit
$m$	Number of overall users
$n$	Number of overall items
$k$	Number of items to recommend
$\mathcal{U} = \{u_1, \dots, u_m\}$	Set of users
$\mathcal{I} = \{i_1, \dots, i_n\}$	Set of items
$\mathbf{X} \in \{0, 1\}^{m \times n}$	User-item interaction matrix
$x_{u,i} \in \{0, 1\}$	User-item feedback
$\Theta$	Set of model parameters
$\hat{\mathbf{X}}(\Theta)$	Scoring function
$\hat{x}_{u,i}(\Theta) \in [0, 1]$	User-item predicted interest
$\mathcal{Y}_{u,k}$	Recommendations list
$\mathcal{T}(\mathcal{Y}_{u,k})$	Utility function
$\rho_{u,i}$	User-item interaction utility

missing entries of  $\mathbf{X}$ . The scoring function is parameterized by a set  $\Theta \in \mathbb{R}^o$  of model parameters<sup>3</sup> - where  $o$  is the number of parameters. Hence,  $\hat{x}_{u,i}(\Theta)$  represents the expected interest of the user toward an item he or she has never interacted with.

In the general top- $k$  recommendation problem (Adomavicius and Tuzhilin, 2005), an ordered list  $\mathcal{Y}_{u,k}$  of  $k$  items to be recommended to

<sup>3</sup> For some algorithms, such as User-Based Collaborative Filtering based on Nearest-Neighbor techniques (Nikolakopoulos et al., 2022), we assume  $\Theta = \emptyset$  since there are no model parameters.



each user  $u$  is determined optimizing a specific *utility function*  $\mathcal{T}(\mathcal{Y}_{u,k}) : \mathcal{Y}_{u,k} \rightarrow \mathbb{R}$ . More formally:

$$\operatorname{argmax}_{\mathcal{Y}_{u,k}} \mathcal{T}(\mathcal{Y}_{u,k}) \quad (1)$$

The utility function can be implemented in arbitrary ways (e.g., including relevance, profitability, and other aspects).

Given  $\rho_{u,i}$  as the utility of the user-item interaction, the vast majority of the studies in the RSs literature operationalize the utility function as:

$$\mathcal{T}(\mathcal{Y}_{u,k}) = \sum_{i \in \mathcal{Y}_{u,k}} \rho_{u,i} \quad (2)$$

optimizing directly:

$$\operatorname{argmax}_{\mathcal{Y}_{u,k}} \sum_{i \in \mathcal{Y}_{u,k}} \hat{x}_{u,i}(\Theta) \quad (3)$$

and thus considering the utility of the potential interaction as the expected interest, i.e.,  $\rho_{u,i} = \hat{x}_{u,i}(\Theta)$ .

However, although this user-focused utilitarian conception is currently the most widely used one in the literature, a recommendation provider may have different goals. In the context of ECRSs, instead, the utility functions may be operationalized considering the item's price  $p_i$ , and profit  $v_i = p_i - c_i$ , where  $c_i$  is the item's cost. For example, algorithms belonging to the profit-aware subdomain that we discuss in Section 4.3 are often developed to find the most profitable, yet relevant, items for the company, and these may clearly differ from the *most* relevant ones.

#### 4.1. Price-sensitivity methods

Price is one of the variables that most influence customers' buying behavior (Lichtenstein et al., 1993; Ali and Anwar, 2021). Accordingly, many studies in the literature (Ge et al., 2014; Chen et al., 2017; Greenstein-Messica and Rokach, 2018; Zheng et al., 2021; Kompan et al., 2022) propose algorithms to explicitly consider customers' price sensitivity, as more accurate and relevant recommendations (i.e., in terms of being in the right price range) could directly increase the probability of purchase and thus lead to higher sales revenue for the organization. Below, we give some insights on how these methods work by discussing a set of selected articles.

##### 4.1.1. In-processing price-sensitivity methods

Most of the approaches used to generate price-sensitive recommendations are based on in-processing algorithms. The main characteristic of these algorithms is that price sensitivity is incorporated directly into the model.

In particular, this methodology proved particularly flexible to be applied to the well-known *Matrix Factorization* (MF) (Koren and Bell, 2021; Koren et al., 2009) model. The original model estimates the expected interest of the user toward a given item via the dot product of latent factor vectors. These are traditionally learned through a dimensionality reduction algorithm applied to the user-item interaction matrix. Considering price-sensitive methodologies based on MF, for example, one paper (Ge et al., 2014) proposes to incorporate cost factors<sup>4</sup> into the model's objective function to generate more accurate travel tour recommendations. The experiments reported by the authors indicate that explicitly incorporating cost factors improves the overall accuracy of the recommendations when compared with a plain MF model. Also, extending MF, other papers in the literature (Chen et al., 2014, 2017) propose incorporating customers' price preferences explicitly into the objective function through the use of particular regularizers. However, whereas previously the purpose was to enhance

the overall performance of the system, here the study is about the use of price preferences to make recommendations in product categories that the user has never explored (*transfer learning*). In particular, according to the authors, generating recommendations for customers' unexplored product categories can cause significant performance drops (−40%) if traditional algorithms are used, since the learned product user preferences are difficult to transfer from one category to another. Instead, explicitly incorporating customers' price preferences into the objective function can help to significantly improve (+43%) performance on unexplored categories compared to state-of-the-art baselines.

Other studies in the literature (Greenstein-Messica et al., 2017; Greenstein-Messica and Rokach, 2018; Umberto, 2015) propose incorporating customers' price preferences within existing *context-aware* recommendation algorithms (Kulkarni and Rodd, 2020). In particular, an experimental study (Umberto, 2015) proposed adapting collaborative filtering algorithms by integrating price as an additional dimension of the well-known multi-dimensional context-aware recommendation model (Adomavicius and Tuzhilin, 2010). As the study found, the integration of price information allows the accuracy of recommendations to be increased on average. However, the way the price is set could impact business performance. Indeed, a price-sensitive RS could increase the accuracy of predicting cheap items and simultaneously decrease the accuracy of predicting more expensive items, thus yielding negative effects on corporate profitability. Similar results were also found by another study with real customers in the food & beverage field (Greenstein-Messica et al., 2017). According to the study, explicitly incorporating discount sensitivity into the algorithms can help to significantly improve performance in a coupon recommendation task when compared to the CAMF method (Baltrunas et al., 2011), i.e., a context-aware variant of matrix factorization. Specifically, in the domain of location-based deals, the analysis shows that the most important feature for predicting purchase probability is the discount-to-distance ratio: the higher the discount offered by the store, the more likely the customer is to travel longer distances to obtain it. However, as is well known in the literature, context variables often depend on the considered business domain. In particular, eBay.com has some unique characteristics (Greenstein-Messica and Rokach, 2018). In this multi-seller platform, the same products are offered at various prices simultaneously by various sellers with different reputation scores. According to a study (Greenstein-Messica and Rokach, 2018), in this business domain, incorporating customers' *willingness-to-pay* (WTP), discounting, and seller reputation features into a context-aware recommender can help to significantly improve the accuracy of predictions, with an 84% improvement over MF models.

In addition, recent studies (Zheng et al., 2020, 2021; Zhang et al., 2022b) propose incorporating customers' price preferences into algorithms by exploiting Graph Neural Networks (GNNs) (Gao et al., 2023). Specifically, in two related studies (Zheng et al., 2020, 2021), it is proposed to construct a GNN-based recommender by building a heterogeneous graph consisting of different types of nodes: customers, items, prices, and product categories. The key idea is to propagate price influence from prices to users by leveraging items as a bridge so that price preferences are implicitly encoded into the embeddings. The use of price-sensitive GNNs is also exploited in the field of session-based recommendations (Zhang et al., 2022b). For all studies based on GNNs (Zheng et al., 2020, 2021; Zhang et al., 2022b), the models are able to generate slightly more relevant recommendations than the baselines. However, as various authors pointed out, it is difficult to handle heterogeneous information and model complex relationships underlying customer buying behavior, and research still offers many opportunities to develop better-performing models that can fully exploit the potential of GNN-based algorithms.

<sup>4</sup> Note that here we respect the original paper's terminology by referring to the cost, but actually the cost for the user is simply the item's price.



**Table 5**  
Price-sensitive re-ranking methods.

Ref	Re-ranking method
Shiu et al. (2018)	$\operatorname{argmax}_{\mathcal{Y}_{u,k}} \sum_{i \in \mathcal{Y}_{u,k}} \hat{x}_{u,i}(\Theta) \cdot s_{u,i}(\Phi) \quad (4)$
Wadhwa et al. (2020) <sup>a</sup>	$\operatorname{argmax}_{\mathcal{Y}_{u,k}} \sum_{i \in \mathcal{Y}_{u,k}} w_1(\Psi) \cdot \hat{x}_{u,i}(\Theta) + w_2(\Psi) \cdot s_u(\Phi) \quad (5)$
Kompan et al. (2022)	$\operatorname{argmax}_{\mathcal{Y}_{u,k}} \sum_{i \in \mathcal{Y}_{u,k}} \hat{x}_{u,i}(\Theta) \cdot \left( \left( 1 + \log_{10} \left( 0.1 + \frac{0.9 \cdot p_i}{c_i} \right) \right)^\beta + \left( 1 + \log_{10} \left( 0.1 + \frac{0.9 \cdot p_i}{\bar{p}^u} \right) \right)^\gamma \right) \quad (6)$

<sup>a</sup> The formula captures the main essence of the described approaches.

#### 4.1.2. Post-processing price-sensitivity methods

A number of price-sensitive recommendation algorithms also make use of post-processing methods. The latter are primarily re-ranking algorithms, which can be applied on top of any price-agnostic recommender baseline.

In this domain, it is proposed, for example, to generate recommendations by weighting the expected interest  $\hat{x}_{u,i}(\Theta)$  by the price-sensitivity  $s_{u,i}(\Phi)$ . The latter is a particular variable, learned through a different model parameterized by  $\Phi$ , indicating how price-sensitive a given user is to a given item (Eq. (4)) (Shiu et al., 2018). A similar approach is also proposed in another study (Wadhwa et al., 2020). However, in this case, the price-sensitivity variable  $s_u(\Phi)$  depends only on the customer and not on the item (Eq. (5)). In addition, it is necessary to use another regression model (parameterized by  $\Psi$ ) to learn how to properly weigh (through  $w_1(\Psi)$ ,  $w_2(\Psi)$  coefficients) the price-sensitivity with the user's expected interest. Both studies show that through the use of price-sensitivity algorithms, more relevant recommendations can be obtained.

Recently, another research (Kompan et al., 2022) proposes a hybrid approach (Eq. (6)) combining the price-sensitive and the profit-aware<sup>5</sup> subdomains. This approach weighs the expected interest  $\hat{x}_{u,i}(\Theta)$  by balancing a user price preference factor  $\frac{p_i}{\bar{p}^u}$  with a profitability factor  $\frac{p_i}{c_i}$ , where  $\beta, \gamma \in [-1, 1]$  in Eq. (6) are regularization parameters. In particular, considering  $\bar{p}^u$  as the average user price, the first factor captures the difference between the customer's typical price level and the actual item's price. The second factor,  $\frac{p_i}{c_i} = 1 + \frac{v_i}{c_i}$ , captures how much an item's sale is able to repay the underlying cost and bring profit to the organization. In this way, it becomes possible to effectively balance the interests of customers with those of the organization because the increase in profitability that traditionally adversely affects the relevance of recommendations is more than offset by the increase in the latter due to the influence of price preferences.

In Table 5, we formally characterize the three discussed price-sensitive re-ranking methods.

#### 4.2. Economic utility modeling methods

In the economic literature (McConnell and Brue, 2020), user behavior is often modeled using utilitarian theories to construct systems that can describe and/or optimize certain dynamics. According to the *Rational Choice Theory* (RCT), at each time instant, a rational user, when faced with a set of alternatives, will choose those with the highest utility for him or her (Scott, 2000). Accordingly, many studies in the literature (Wang and Zhang, 2011; Ge et al., 2019; Zhao et al., 2017) propose algorithms that explicitly consider the customer's utilitarian behavior to generate more useful recommendations that can in turn increase conversion rates and profitability. Below we give some insights on how these methods work by discussing a few selected articles focused, respectively, on multi-attribute, repurchase, and complementary recommendations.

In the field of RSs, many studies in the literature assume that the utility  $\rho_{u,i}$  of a product to a customer depends on his or her purchase history (Wang and Zhang, 2011). Most existing RSs recommend for each user  $u$  a list  $\mathcal{Y}_{u,k}$  consisting of the top- $k$  items (Eq. (3)) with the highest predicted scores  $\hat{x}_{u,i}(\Theta)$ . The list  $\mathcal{Y}_{u,k}$  is traditionally selected from a set of items with which the user has never interacted before. Interpreting this assumption from the perspective of economic utility theory (Eq. (7)) (Wang and Zhang, 2011), then, the utility  $\mathcal{T}(\mathcal{Y}_{u,k})$  of a recommendation  $\mathcal{Y}_{u,k}$  is nothing but the sum of the predicted scores, i.e.,  $\rho_{u,i} = \hat{x}_{u,i}(\Theta)$ . In this case, a recommendation  $\mathcal{Y}_{u,k}$  generated by optimizing the total utility of a set of  $k$  recommended items optimizes the expected user interest estimated by any recommendation algorithm.

However, in addition to the previous utility definition, alternative definitions are recently emerging in the literature. For example, in the field of *Multi-Criteria Recommendation Systems* (MCRS) (Al-Ghuribi and Mohd Noah, 2019), in the presence of a set  $\mathcal{G}$  of attributes associated with items, various studies in the literature (Huang, 2011; Dörner and Scholz, 2013; Deng, 2015; Scholz et al., 2015; Zheng, 2019) propose to generate recommendations by exploiting the *Multi-Attribute Utility Theory* (MAUT) (Keeney and Raiffa, 1993). MAUT is one of the most widely used utilitarian theories in decision making, which aims to weigh a set of relevant variables to determine the overall utility of each alternative. In the context of recommendations, in particular, the overall optimized utility (Eq. (8)) in this case depends on the utility  $\rho_{i,g}$  of the single attribute  $g$  of item  $i$ , and a weight  $f_{u,g}$  that each user can provide to indicate the importance of that attribute.

Other studies focus on the problem of repeated purchase recommendations (Wang and Zhang, 2011; Zhang et al., 2016; Zhao et al., 2017; Ge et al., 2019). Unlike traditional RSs, algorithms developed for this task generate recommendations by also considering items that the user already purchased in the past. In particular, it is observed that the repurchase cycle of some products may follow the *Law of Diminishing Marginal Utility* (Wang and Zhang, 2011; McConnell and Brue, 2020). According to this theory, many products have decreasing utility for the user as the quantity of purchased products increases (e.g., computers, cell phones), while others, instead, are likely to be purchased frequently over time (e.g., baby diapers, pet food). Using the standard utilitarian criterion in Eq. (7) it is not possible to model this behavior. Indeed, in this case, the usefulness of recommendations for the user highly depends on the quantity  $q_{u,i}$  of item  $i$  purchased by him or her until a specific time. In this context, promising results can be obtained by modeling the repurchase cycle through the *Constant Elasticity of Substitution Utility Function* (Uzawa, 1962). This allows the decreasing marginal utility of product  $i$  to be properly modeled through a parameter  $\xi_i \in [0, 1]$  associated with item  $i$  (Eq. (9)). This parameter can be learned by extending the MF objective function. In this way, the algorithm can explicitly consider the decreasing utility of certain products for the user and generate more relevant recommendations.

With similar methodologies, other utilitarian functions are also used in the literature to model customer purchasing behavior (Zhang et al., 2016; Zhao et al., 2017; Ge et al., 2019). However, these studies focus on different objectives. For example, one study (Zhang et al., 2016) proposes three different business cases (i.e., e-commerce, P2P lending, freelancing) that exploit the *King-Plosser-Rebelo Utility Function* (Eq. (10)) to optimize the *Total Surplus*, i.e., an indicator that considers both the usefulness of the recommendations for the customer and the profit for the producer. Another study (Zhao et al., 2017) in contrast propose to use the *Multi-Product Utility Function* (Eq. (11)) in order to also consider any complementary and substitutability relationships among the recommended products.<sup>6</sup> In the equation, the variables  $a_{i,j}$

<sup>6</sup> Note that alternative approaches for generating complementary recommendations that are not based on particular utility theories and that do not explicitly optimize business KPIs are available in the literature, e.g., Hao et al. (2020), Zhang et al. (2018) and Sun et al. (2017).

<sup>5</sup> We discuss profit-aware methods in Section 4.3.

**Table 6**  
Economic utility functions from rational choice theory.

Ref	Name	Utility function
Wang and Zhang (2011)	Standard	$\mathcal{T}(\mathcal{Y}_{u,k}) = \sum_{i \in \mathcal{Y}_{u,k}} \rho_{u,i}$ (7)
Huang (2011)	Multi-attribute	$\mathcal{T}(\mathcal{Y}_{u,k}) = \sum_{i \in \mathcal{Y}_{u,k}} \sum_{g \in G} f_{u,g} \cdot \rho_{i,g}$ (8)
Wang and Zhang (2011) <sup>a</sup>	Constant elasticity of substitution	$\mathcal{T}(\mathcal{Y}_{u,k}) = \sum_{i \in \mathcal{Y}_{u,k}} \rho_{u,i} \cdot q_{u,i}^{\frac{1}{\sigma}}$ (9)
Zhang et al. (2016)	King-Plosser-Rebelo	$\mathcal{T}(\mathcal{Y}_{u,k}) = \sum_{i \in \mathcal{Y}_{u,k}} \rho_{u,i} \cdot \ln(1 + q_{u,i})$ (10)
Zhao et al. (2017)	Multi-product	$\mathcal{T}(\mathcal{Y}_{u,k}) = \frac{1}{ \mathcal{Y}_{u,k} } \sum_{i,j \in \mathcal{Y}_{u,k}: i \neq j} \left( a_{i,j} \cdot q_{u,i}^{1-b_{i,j}} + (1 - a_{i,j}) \cdot q_{u,j}^{1-b_{i,j}} \right)^{\frac{1}{1-b_{i,j}}}$ (11)
Ge et al. (2019)	Marginal utility per Dollar	$\mathcal{T}(\mathcal{Y}_{u,k}) = \sum_{i \in \mathcal{Y}_{u,k}} \frac{\tanh(\rho_{u,i}) \cdot r_{i,u}}{(1 + q_{u,i}) \cdot \sigma(p_i)}$ (12)

<sup>a</sup> The formulas capture the main essence of the described approaches.

and  $b_{i,j}$  are additional parameters that the recommendation algorithm can jointly learn with the latent factors to model the indifference curves between pairs of products, i.e., how much the increase in one product affects the relative marginal utility of another product. Finally, one study (Ge et al., 2019) proposes using the *Marginal Utility per Dollar Function* (Eq. (12)). This function considers the price  $p_i$  of item  $i$  and a risk attitude coefficient  $r_{i,u}$  to model customers' risk-aversion, i.e., the tendency of consumers to spend only a small portion of their total wealth on a single purchase.

In Table 6, we formally characterize the utility criteria discussed above.

#### 4.3. Profit-aware methods

Profit is one of the most important business KPIs for a successful enterprise (Teece, 1981). Accordingly, many studies in the literature (Chen et al., 2008; Kompan et al., 2022; Goyal and Lakshmanan, 2012; Li et al., 2021; Nemati and Khademolhosseini, 2020; Concha-Carrasco et al., 2023) propose profit-aware recommendation algorithms to directly optimize the firm's profitability. Below we give some insights on how these methods work by discussing a few selected articles.

##### 4.3.1. In-processing profit-aware methods

Profit-aware in-processing approaches in the literature are quite heterogeneous, scattered, and there are several parallel lines of research. Below, we offer a brief overview of major research directions in this area.

Some early studies (Piton et al., 2011; Huang et al., 2013; Yang et al., 2017) exploit *Association Rules* (Hipp et al., 2000). According to this particular methodology (Park et al., 2012), recommendations are generated through a frequentist approach based on statistical support and confidence constructs (Osadchiy et al., 2019). One of Amazon's most prominent recommenders, i.e., “customers who bought this item also bought”, is seemingly based on association rules. In particular, many studies in the literature (Wang et al., 2002b,a; Wang and Zhou, 2005; Chen et al., 2007b) propose to generate association rules while also optimizing profitability. The main methods incorporate profit considerations when weighting the rules (Cai et al., 1998). However, unlike modern RSs based on collaborative and content-based filtering algorithms, association rules (Wang et al., 2002b) are not personalized, i.e., different users do not get different recommendations. In addition, association rules may generally face challenges when the total number of recommendable items is very large.

Other studies (Brand, 2005; Akoglu and Faloutsos, 2010; Qu et al., 2014; Li et al., 2017) propose graph-based approaches. In particular, two works (Akoglu and Faloutsos, 2010; Li et al., 2017) focus on social networks. The proposed algorithms are designed to explicitly optimize

the value of link recommendations. For example, one of those works (Li et al., 2017), which considered not only the likelihood of a potential link for the user but also the value of that link for a social network operator in economic terms (i.e., revenues and costs), demonstrated promising results in optimizing the platform's revenue streams from advertising. Another relatively recent approach based on graphs (Qu et al., 2014) is developed specifically for the taxi industry. In this particular application domain, if we assume an hourly rate, a taxi driver's profit depends solely on the hours billed to customers: simply put, it is critical for a taxi driver to minimize the distance to find a customer and maximize the distance traveled with a customer on board. The proposed algorithm recommends pick-up points for taxi drivers in order to maximize the profit of driving routes while balancing the potential congestion resulting from multiple requests from different customers at the same location.

More recently, a study (Cai and Zhu, 2019) proposes a profit-aware RS based on collaborative filtering. The algorithm is based on an extension of the well-known neighbor selection criterion of the user-based nearest-neighbor collaborative filtering model (Nikolakopoulos et al., 2022). The original algorithm calculates the predicted score based on a weighted sum of similarities between users belonging to a given neighborhood, usually based on correlation criteria. The authors of Cai and Zhu (2019) instead propose to calculate the predicted scores by selecting the neighbors that would allow the generation of the highest value-weighted expected interest. Although the focus of the paper is on shilling attacks, i.e., attacks by malicious users who generate biased ratings to influence recommendations for their interests, the subprocedure for selecting the most valuable users can be used to generate more profitable recommendations.

Other recent approaches (Wu et al., 2018; Lin et al., 2019; Li et al., 2021) are based on *Learning To Rank (LTR)* (He et al., 2008). This is a well-known technique in *Information Retrieval (IR)* (Kobayashi and Takeda, 2000; Bellogin and Said, 2019). IR algorithms aim to help users to find the most relevant items based on specific search queries. In particular, one study (Wu et al., 2018) uses this methodology in a product search application context. The proposed algorithm integrates the price into the objective function in order to optimize the overall sales revenue of an e-commerce. This technique is later applied (Lin et al., 2019; Li et al., 2021) also to generate recommendations without the need to anchor them to an underlying search query. For example, one study (Lin et al., 2019) proposes a multi-objective algorithm that is able to optimize multiple objective functions simultaneously through LTR. The algorithm is Pareto-efficient, i.e., it optimizes each objective (e.g., CTR and GMV<sup>7</sup>) one at a time, with the constraint that no single objective can be further improved without affecting others.

<sup>7</sup> We provide the definition of the most frequently used online metrics in Table 10.

**Table 7**  
Profit-aware re-ranking methods.

Ref	Re-Ranking Method
Chen et al. (2008)	$\operatorname{argmax}_{\mathcal{Y}_{u,k}} \sum_{i \in \mathcal{Y}_{u,k}} \hat{x}_{u,i}(\Theta) \cdot v_i \quad (13)$
Das et al. (2009)	$\operatorname{argmax}_{\mathcal{Y}_{u,k}} \sum_{i \in \mathcal{Y}_{u,k}} \hat{x}_{u,i}(\Theta) \cdot v_i \quad (14)$
Wang and Wu (2012) <sup>a</sup>	$\begin{aligned} &\text{s.t. Dice}(\hat{x}_u(\Theta), \hat{x}_u(\Theta)^T \mathbf{v}) \geq \eta \\ &\operatorname{argmax}_{\mathcal{Y}_{u,k}} \sum_{i \in \mathcal{Y}_{u,k}} v_i \quad (15) \end{aligned}$
Jannach and Adomavicius (2017) <sup>a</sup>	$\begin{aligned} &\text{s.t. } \hat{x}_{u,i}(\Theta) \geq \zeta, \quad p_i \leq \lambda_u \\ &\operatorname{argmax}_{\mathcal{Y}_{u,k}} \sum_{i \in \mathcal{Y}_{u,k}} \hat{x}_{u,i}(\Theta) \cdot v_i \quad (16) \end{aligned}$
Ghanem et al. (2022)	$\begin{aligned} &\operatorname{argmax}_{\mathcal{Y}_{u,k}} \sum_{i \in \mathcal{Y}_{u,k}} \delta \cdot \hat{x}_{u,i}(\Theta) + (1 - \delta) \cdot v_i \quad (17) \end{aligned}$
Malthouse et al. (2019b) <sup>a</sup>	$\begin{aligned} &\operatorname{argmax}_{\mathcal{Y}} \sum_{u \in \mathcal{U}} \sum_{i \in \mathcal{I}} \delta \cdot y_{u,i} \cdot \hat{x}_{u,i}(\Theta) + (1 - \delta) \cdot y_{u,i} \cdot d_{u,i} \quad (18) \\ &\text{s.t. } \sum_{i \in \mathcal{I}} \mathbb{I}(y_{u,i} \cdot d_{u,i} > 0) \leq l \quad (\forall u \in \mathcal{U}) \end{aligned}$

<sup>a</sup> The formulas capture the main essence of the described approaches.

Finally, some studies (Nemati and Khademolhosseini, 2020; Concha-Carrasco et al., 2023) propose using profit-aware multi-objective evolutionary algorithms (Horváth and de Carvalho, 2017; Zheng and Wang, 2022). One of these (Nemati and Khademolhosseini, 2020) is based on *Non-dominated Sorting Genetic Algorithm II* (NSGA-II). A more recent one (Concha-Carrasco et al., 2023) is based on *Multi-Objective Artificial Bee Colony* (MOABC). In these cases, the optimization target is a combination of the item's profit and the user's expected interest. Both algorithms obtained very promising offline results on the overall profit improvement, although the comparison was performed exclusively with a traditional user-based collaborative filtering algorithm (Nikolakopoulos et al., 2022).

#### 4.3.2. Post-processing profit-aware methods

In the context of this survey, many profit-aware approaches rely on post-processing re-ranking methods. As mentioned earlier, these approaches consider the recommender baseline as a black box and generate recommendations by exploiting a combination of certain heuristics.

All examined profit-aware approaches are based on a simple but important assumption (Jannach and Adomavicius, 2017; De Biasio et al., 2023b): the items most relevant to the user are often not those of the highest business value to the organization. Consequently, prioritizing the highest-profit items in recommendations would allow for increased business profitability as a result of actual user purchases of those items. In one of the earliest approaches (Chen et al., 2007a, 2008) it is proposed to weight the probability of purchase (i.e., the estimated expected interest) by profitability in order to maximize an average expected profit (Eq. (13)). This approach should make it possible to provide more profitable recommendations than those generated by traditional RSs. Experiments in a synthetic dataset based on a subset of groceries transactions show encouraging results: the proposed algorithm was able to increase profitability without excessively impacting the relevance of recommendations. However, as also reported by the authors (Chen et al., 2007a, 2008), the interests of customers and the organization must be balanced appropriately. In fact, the organization could risk losing loyal customers should they feel dissatisfied with overly biased recommendations toward higher-value items and decide to leave the platform.

To mitigate this drawback, and thus to avoid providing completely irrelevant recommendations, various studies propose more or less straightforward extensions of Eq. (13) based on constrained optimization techniques. One of the earliest papers (Das et al., 2009) proposes a constrained re-ranking method based on the *Dice* coefficient (Eq. (14)). This can help prevent the system from providing recommendations that are too dissimilar from the original ones based on a threshold  $\eta$ . However, the study is based on various simplifying assumptions and does not provide an empirical evaluation of the approach. In two

related studies (Wang and Wu, 2009, 2012) instead, it is proposed to maximize profitability under customer satisfaction and budget constraints (Eq. (15)), where  $\zeta$  and  $\lambda_u$  are two thresholds used to keep the probability of purchase and the price of items within certain ranges, respectively. In particular, an expert system is proposed where different optimization goals can be specified in order to optimize profitability or balance profitability and satisfaction in order to achieve a win-win situation for suppliers and customers. A similar variant of this approach (Eqs. (16), (17)) is also proposed in two related studies (Jannach and Adomavicius, 2017; Ghanem et al., 2022) where the short- and long-term profit-relevance tradeoff is investigated through the use of simulations. In Eq. (17),  $\delta \in [0, 1]$  is a regularization parameter.

In addition, other studies (Malthouse et al., 2019a,b; Zhang et al., 2017b) propose algorithms to address the problem of sponsored recommendations. In this scenario, a supplier who decides to sponsor its products pays the platform for each user interaction. One study (Malthouse et al., 2019b) in particular proposes a multi-objective post-processing re-ranking algorithm (Eq. (18)). In the equation,  $y_{u,i}$  is a decision variable ( $y_{u,i} = 1$  iff  $i \in \mathcal{Y}_{u,k}$ ),  $d_{u,i}$  is the ad revenue that the organization gets from suppliers if the user interacts with the item, and  $l < k$  is the maximum number of sponsored items that can be included in the recommendation list. The algorithm is designed to balance the recommendation of high ad revenue sponsored items with the user's interests.

In Table 7, we formally characterize the profit-aware re-ranking methods discussed above.

#### 4.4. Promotional methods

Promotional methods (Morgan et al., 2019; Michalis and Michael, 2013) aim to increase sales figures by promoting products and services to the most appropriate customer segments. We identify three main strategies in the RSs literature that can be used to optimize profit and related business KPIs. *Pricing methods*, can be used to offer products at a discounted price or to strategically adjust prices in order to increase the market demand. *Bundling methods*, are special pricing methods that are applied to product bundles. *Brand-awareness methods*, finally, can be used to focus customers' attention on the organization's products in order to generate extra sales. Below we give some insights on how these methods work by discussing a few selected articles in each category.

##### 4.4.1. Pricing methods

As discussed earlier in Section 4.1, price is one of the most influential variables of customer buying behavior, and considering this variable explicitly would allow for recommendations more in line with customers' interests. However, while the previous section focuses on customer-oriented methodologies that integrate price sensitivity as



additional information in order to generate more relevant recommendations, in this section we instead discuss promotional techniques that an organization might want to apply to incentivize the purchase of certain products by strategically setting the prices (Bergemann and Ozmen, 2006; Ghoshal et al., 2021). In the following, we describe two organizational strategies referring to: (a) *occasional discounting*; (b) *personalized dynamic pricing*.

One of the most commonly used promotional strategies to incentivize product purchases is to offer occasional discounts (Chen et al., 1998), for example at certain times of the year (e.g., winter sales) or special events (e.g., Black Friday). In the context of RSs many studies (Wu and Teng, 2011; Jannach and Ludewig, 2017; Wang et al., 2020; Sato et al., 2015; Jiang and Liu, 2012; Jiang et al., 2015; Guo et al., 2020) aim to generate recommendations while considering discounts. Some studies propose, for example, to use re-ranking algorithms (Jannach and Ludewig, 2017) to promote products on sale or in-processing methods (Wang et al., 2020) based on adaptations of MF-based models to explicitly consider customers' discount sensitivity (Sato et al., 2015). Another method is proposed in two related studies (Jiang and Liu, 2012; Jiang et al., 2015). In particular, as noted by the authors, there may be inter- and cross-category effects when discount products are bought. Thus, especially in e-commerce, organizations can exploit RSs to incentivize customers to buy discount products but also those products that are related to them but not on sale (e.g., camera on sale and full-price lens). A similar analysis is also made (Guo et al., 2020) to determine the optimal shipping-fee discount to attract customers to the platform and encourage them to purchase products related to the discounted ones.

While discounts may be occasional and the same for all customers, some methodologies are proposed in the RSs literature to generate dynamic customer-specific prices in order to strategically promote certain products and generate higher profits. In this context, some initial studies (Backhaus et al., 2010a,b) propose to use survey-based techniques (*conjoint analysis*) to estimate customer WTP (recall Section 4.1.1) and filter items that are priced higher than WTP in the ranking. The authors also discuss some possible configurations of the algorithm to set the prices based on WTP in order to generate more profit for the organization. However, the proposed pricing model is only theoretical as it is not validated by empirical experiments. Another study (Kamishima and Akaho, 2011) proposes a system that classifies customers based on whether they would buy products only if discounted or not. Based on the type of customer, the system can offer a discount in order to incentivize purchases. However, as discussed later (Massoud and Abo-Rizka, 2012), the study is based on assumptions that are not feasible in practice: all products have the same price; only two price values are available (i.e., standard and discounted price). Another work (Zhao et al., 2015) proposes a different methodology. The study focuses on a lottery-based mechanism that aims to obtain the exact WTP for one subset of products and then to exploit this information to predict the WTP for another subset of products. In this way, the system can offer a personalized promotion to increase the conversion rate of the latter product subset. The authors report significant results on the potential ability of this system to increase profit over conventional systems. However, the experiments are based on a user study with a low number of users. Finally, another study (Adelnia Najafabadi et al., 2022) proposes a dynamic personalized pricing RS for information goods (e.g., digital movie rentals). These goods differ from physical goods in that their production and distribution costs are negligible and they can be copied, rented, and resold easily. In this context, traditional markup-based pricing methods (i.e., cost plus margin) are not effective because there is no true underlying unit cost. The proposed system first classifies customers according to their WTP and quality sensitivity (e.g., whether they prefer a premium version of the same product). Then it calculates a personalized price to incentivize purchase.

#### 4.4.2. Bundling methods

One frequently used promotional strategy (Venkatesh and Mahajan, 2009) to increase sales revenue of certain products is to offer them at a discount if purchased in bundles (Harlam et al., 1995). In the literature (Yan and Bandyopadhyay, 2011) it is proposed, for example, to include in the bundles: (a) products that are complementary to each other in order to incentivize cross-selling; (b) products that are uncorrelated, for example, to clear the stock in the warehouse; (c) the same product in multiple quantities (e.g.,  $2 \times 1$  promotion). Specifically, in RSs research (Li et al., 2020b), one branch of the literature focuses on recommending bundles to optimize profit by exploiting price modeling techniques. The other branch, in contrast, does not exploit such techniques and focuses solely on optimizing relevance.<sup>8</sup> In this review, we focus only on bundling approaches that aim to explicitly optimize business KPIs.

Concerning price modeling bundle recommendation techniques, two related earlier studies (Garfinkel et al., 2006, 2008) focus on the development of a shopbot (i.e., comparison shopping agents) capable of offering bundles at a discounted price based on an integer linear programming model. The proposed algorithm is validated using data from Amazon.com and Buy.com reporting significant results from the perspective of potential economic savings of price-sensitive bundle purchasing customers. However, the data sample used is very small, and optimization of business KPIs is not explicitly considered. In contrast, two other studies (Jiang et al., 2011; Zhu et al., 2014) leverage similar integer programming-based approaches to recommend bundles with the goal of optimizing profitability (Jiang et al., 2011) or any business objective (Zhu et al., 2014). In particular, considering the case where the bundle can be created directly by the customer by selecting the products of his or her preference, the first study (Jiang et al., 2011) proposes a multistage approach that can dynamically determine the price of the added products in real-time with the goal of maximizing profits for the organization. In contrast, the second study (Zhu et al., 2014) investigates how to incorporate product compatibility and potential cost savings to generate bundles that, if recommended, could optimize certain business objectives (e.g., profitability, revenue, and others). Both studies report results regarding the potential ability of the proposed systems of increasing profitability and conversion rates. In addition, two other approaches (Beladev et al., 2016; Ettl et al., 2020) are proposed recently. The first approach (Beladev et al., 2016) is based on a collaborative filtering algorithm that integrates demand estimation and price modeling techniques to make recommendations with the goal of jointly maximizing purchase probability and sales revenue considering the customer WTP. The second approach (Ettl et al., 2020) is based on an algorithm that can recommend bundles with customized discounts to customers considering also inventory levels. However, in the former case, the bundle does not offer an additional discount over the full price of the individual products. Instead, the bundle is created exclusively so that the total price of the products inside it is aligned with the customer's WTP to meet his or her price preferences. In the latter case, on the other hand, the evaluation is based on a simulation focused on the aviation industry with a large number of assumptions.

#### 4.4.3. Brand-awareness methods

Some methods in the literature can be used to promote the organization's products and services, raise brand awareness, and increase profitability in the long run. These methods can be interpreted by

<sup>8</sup> Relevance-based bundling algorithms (Sun et al., 2022) can be based for example on association rules (Yang and Lai, 2006; Fang et al., 2018; Jiao and Zhang, 2005), graph-based approaches (Liu et al., 2017; Ge et al., 2017; Liu et al., 2017; Deng et al., 2020; Bai et al., 2019), GNNs (Chang et al., 2020; Agarwal et al., 2022; Chang et al., 2023) and transformers (Avny Brosh et al., 2022).



referring to the sales funnel (Venermo et al., 2020). The sales funnel is a theoretical model that describes the customer journey in different stages according to the type of customer interaction with the organization (Paschen et al., 2020). Depending on the status of the customer in the sales funnel, it might be advisable to design an RS with different purposes.

If the customer has not yet made the first purchase (which is referred to as the prospect state), it might be promising to maximize the conversion rate by closing the first deal as quickly as possible (Karlsson and Nilsson, 2013). At this early stage, recommending the most popular products may not be the best strategy. Since many popular products are commonly purchased together, customers would discover them on their own without the need of a recommendation. Instead, it could be more beneficial to present still popular but unrelated products, optimizing coverage. In this way, it may be possible to attract more customers to the platform and increase the probability they make their first purchase.

Once the customer has made the first purchase, the company can exploit mechanisms to optimize profits in the long-run (Bodapati, 2008; Goyal and Lakshmanan, 2012). One option could be to mainly recommend items with high consumer ratings (Jannach et al., 2010). However, similarly to the previous case, this may not be the best choice either, as many customers might search for and buy such items anyway. Instead, it might be more valuable to stimulate the purchase of products of possible interest that are likely unknown to the customer (Bodapati, 2008), e.g., products that do not fall in the top- $k$  but have medium-high ranking positions. This way, the company may get both the revenue from the purchases of products that the customer would discover on their own without the recommendations, and an additional revenue through the purchases that were triggered by the recommendations. With similar objectives, it might also be worthwhile for the company to leverage an RS (Goyal and Lakshmanan, 2012) to launch a marketing campaign with the purpose of promoting new products in the market. Such a system could be designed to select a set of seed consumers for the marketing campaign such that if these seed consumers provide relatively high ratings, the number of other consumers to whom the new product is recommended is maximized.

#### 4.5. Long-term value sustainability methods

It is very important for organizations to grow sustainably over time (Lumpkin et al., 2010; Rauch et al., 2005). Accordingly, a number of studies in the literature (Hosanagar, 2008; Iwata et al., 2008; Pei et al., 2019) propose recommendation algorithms that consider temporal dynamics to optimize long-term business value. Many of them rely on the *Customer Lifetime Value (CLV)* (Blattberg et al., 2009; Bhaduri and Fogarty, 2016) and other related conceptual models (e.g., *Recency Frequency Monetary - RFM*) from the business literature. CLV represents the expected business value of all future cash flows attributed to a specific customer discounted to the present time.

Similarly to what is found for bundling methods (in Section 4.4.2), some RSs studies propose to exploit CLV to optimize long-term profit (Pei et al., 2019; Iwata et al., 2008) while others exploit it solely to optimize relevance<sup>9</sup> (Shih and Liu, 2008; Tabaei and Fathian, 2012). In this review, we focus only on algorithms that aim to optimize long-term business KPIs. Below we give some insights on how these methods work by discussing a few selected articles. In particular, we first discuss in- and post-processing methods based on supervised learning and then we delve into recent algorithms based on reinforcement learning.<sup>10</sup>

<sup>9</sup> Typically, RSs that rely on CLV-related models to optimize relevance (Liu and Shih, 2005b,a; Shih and Liu, 2005, 2008; Tabaei and Fathian, 2012; Cho et al., 2015; Wang et al., 2009; Karimi et al., 2021; Blattberg et al., 2009) follow a common workflow. Algorithms first group users into similar customer value segments. Then they generate recommendations through association rules or collaborative filtering leveraging this additional information.

<sup>10</sup> Much work has been carried out in the field of reinforcement learning based RSs (Afsar et al., 2022). However, the majority of these papers, e.g., Liu

##### 4.5.1. Post-processing and supervised learning methods for long-term business value optimization

Some studies (Hosanagar, 2008; Hosein et al., 2019; Basu, 2021; Panniello et al., 2016b) propose post-processing algorithms to maximize the long-term business value of recommendations by exploiting heuristic criteria. In particular, Hosanagar (2008) proposes an algorithm following this simple but effective intuition: when a customer trusts an RS, the system should bias the recommendations to increase profitability; instead, when the customer trust is below a certain threshold, the system should recommend the most relevant products to restore trust at the expense of profitability. The original study (Hosanagar, 2008) proposes only a theoretical assessment of the profit surplus that can be generated using this algorithm. However, the algorithm's performance is also evaluated in an online study (Panniello et al., 2016b) and in a recent post-hoc econometric analysis (Basu, 2021). These recent studies demonstrate both the effectiveness of the proposed methods in generating higher sales revenue than a content-based filtering algorithm (Panniello et al., 2016b) and how trust is positively correlated with higher sales revenue (Basu, 2021).

Other approaches based on supervised machine learning algorithms are also studied to explicitly optimize the long-term business value of recommendations. In particular, in two related studies (Iwata et al., 2006, 2008), a recommendation system is proposed to explicitly maximize CLV. The algorithm is designed specifically for subscription-based (Iwata et al., 2006) and transaction-based (Iwata et al., 2008) revenue models. In particular, survival analysis techniques are used to identify frequent purchasing patterns among higher CLV users. Then, recommendations are generated to match those patterns as closely as possible. The algorithms are evaluated using real data from a mobile cartoon provider with a subscription-based revenue model (Iwata et al., 2006) and an online music provider with a transaction-based revenue model (Iwata et al., 2008), both from Japan. However, although results regarding the improvement of the subscription period and the number of items purchased over time are reported, the evaluation is only based on a simulation system of user purchasing behavior.

##### 4.5.2. Reinforcement learning recommendation methods for long-term business value optimization

Recent studies propose methodologies based on *Reinforcement Learning (RL)* for optimizing the long-term business value of recommendations (Sutton and Barto, 2018). RL is a learning approach that aims to learn an optimal policy (i.e., recommendation strategy) based on the sequential interaction between an agent and the environment through trial and error to maximize a reward. This methodology is used many times in the literature (Zou et al., 2019; Zhao et al., 2020; Ji et al., 2021; Guo et al., 2021; Wu et al., 2017; Theocharous et al., 2015; Ju et al., 2017; Pei et al., 2019; He et al., 2022) to optimize CLV.

A few studies propose algorithms to directly optimize profit (Ju et al., 2017; Pei et al., 2019). These studies focus on the transaction-based revenue model where each customer purchase brings a certain profit to the organization. Specifically, in this context, one study (Pei et al., 2019) considers that a certain profit share can be allocated to each user action (i.e., click, add-to-cart, pay). Hence, the overall profitability can be maximized by optimizing the sum of the profit allocated to each user action considering the probability that such an action will occur given the recommendations. Other studies (Zou et al., 2019; Zhao et al., 2020; Ji et al., 2021; Guo et al., 2021; Wu et al., 2017; Theocharous et al., 2015), in contrast, propose algorithms to optimize user engagement, or more generally some strategic interrelated business indicators (He et al., 2022). One study (Theocharous et al., 2015) is based on the advertising revenue model. In this particular context, advertisers are used to pay the platform a certain monetary amount for

et al. (2021, 2020), are not the subject of our analysis, as they do not focus on optimizing business KPIs.

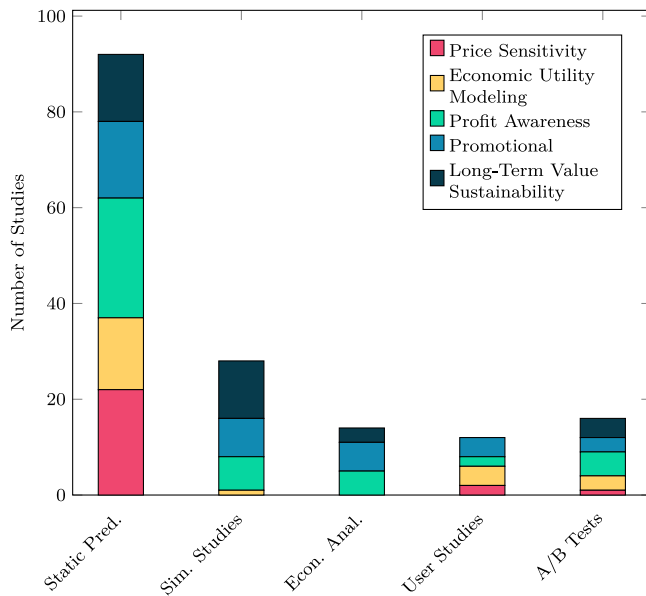


Fig. 4. Distribution of evaluation methods in the surveyed literature organized by dimension of analysis.

each click or conversion generated. Hence, in this case, by optimizing user engagement, profit is directly optimized. Instead, other works (Zou et al., 2019; Zhao et al., 2020; Ji et al., 2021; Guo et al., 2021; Wu et al., 2017), although they similarly propose to optimize user engagement, are not based on advertising revenue models. Therefore, in these cases, the relationship with profitability is indirect, as user engagement positively correlates with retention.

## 5. Evaluation methodologies

In this section, we review the evaluation methodologies used in the surveyed papers. First, we give some insights into the different methodologies that are used to evaluate algorithms. Next, we discuss the metrics used in offline evaluation. Then we discuss the results that have been obtained in the real world from ECRSs algorithms by analyzing in detail those studies that report online performance. Finally, we analyze related topics concerning public datasets and the current level of reproducibility.

### 5.1. Evaluation approaches

In the field of RSs, several methods are proposed to evaluate the performance of algorithms and systems. Depending on the objective of the study, the evaluation may vary in order to assess specific aspects of the recommendations and the system. We identify five methods that are used in the surveyed literature. Some of these are used for offline evaluation (e.g., static predictions, simulation studies, and econometric analyses) (Zhao et al., 2023), while others are used for online evaluation (e.g., user studies, and A/B tests) (Chen, 2017). While offline methods aim to give a plausible estimate of the performance the system could achieve under real circumstances if certain assumptions are verified, online ones are instead based on real user interactions. In Fig. 4 we report the distribution of evaluation methods in the literature according to each DA. As can be seen, offline methods are used more frequently than online ones. Moreover, among offline methods, static predictions is the most frequently used method.

**Static predictions.** The most commonly used evaluation method in the RSs literature is to hide some data (e.g., ratings, interactions) from a particular dataset, train a model on the remaining data, and then predict the hidden data (Jannach and Jugovac, 2019; Zhao et al., 2023). After constructing a dataset that contains all the necessary information,

the adopted standard is to measure the performance of the system with respect to some underlying objectives (Jannach and Adomavicius, 2016; Alslaity and Tran, 2021) with the help of certain metrics. In terms of metrics, given the underlying purposes of ECRSs, the surveyed literature often measures not only relevance prediction metrics (e.g., precision, MRR, NDCG) (Gunawardana et al., 2022), but also business value metrics<sup>11</sup> (e.g., profit, revenue) (Jannach and Jugovac, 2019; Jannach and Adomavicius, 2017; Malthouse et al., 2019b).

**Simulation studies.** While static predictions methods (Zhao et al., 2023) are mainly used to obtain an estimate of RSs performance in the short term, other studies propose to use dynamic simulations to assess long-term performance (Ghanem et al., 2022). The methodology first involves building a simulator to mimic user behavior (Pei et al., 2019; Theocharous et al., 2015; Zhang et al., 2022a). Next, the simulator is used to train and test RSs algorithms on the simulated behavior (Guo et al., 2020; Wu et al., 2017). Simulators are often adopted to evaluate the performance of reinforcement learning-based recommendation algorithms (Afsar et al., 2022) (e.g., RecoGym (Rohde et al., 2018), RecSim (Je et al., 2019)). Moreover, in the surveyed literature there are also simulators (Iwata et al., 2008; Lu et al., 2014; Ghanem et al., 2022) created to evaluate supervised learning algorithms. One of these (Ghanem et al., 2022), based on agent-based modeling, is designed to realistically mimic customer behavior considering various factors known in the literature to have a high correlation with purchase probability (e.g., trust).

**Econometric analyses.** For some algorithms in the surveyed literature (Das et al., 2009; Hosanagar, 2008; Jiang et al., 2015), performance is assessed with the help of econometric analyses (Adamopoulos and Tuzhilin, 2015a; Oestreicher-Singer and Sundararajan, 2012). These are quantitative approaches based on statistical or mathematical methods used to estimate the impact of the system on certain variables of interest (e.g., profit (Hosanagar, 2008)), considering some underlying assumptions. For example, one study (Hosanagar, 2008) investigates the impact of recommendations on corporate profit and consumer welfare by modeling the behavior of a system that considers the simplified case in which the company can sell only two products.

**User studies.** In many cases, the impact of the system on certain factors (e.g., user satisfaction) is difficult to model through offline methods. This occurs because in some cases it is not possible to find a good proxy for the target variable, while in other cases it would be necessary to use a large number of assumptions. Especially when the factors are qualitative and the response is subjective (e.g., perceived fairness), the literature adopts user studies as a research methodology (Chen, 2017). These methods typically involve recruiting a group of users (e.g., through emails or through crowdsourcing platforms like Amazon Mechanical Turk), randomly splitting them into distinct groups, requiring them to perform a particular task (e.g., interacting with an RS designed for the study), observing their (objective) behavior, and asking them about their subjective perceptions. In the surveyed literature these methods are used (Panniello et al., 2016b; Azaria et al., 2013) for example to determine the impact of algorithms on profitability and user trust.

**A/B tests.** When it is necessary to measure the performance of RSs in real-world circumstances, A/B tests are often performed (Chen, 2017). In such tests, two (or more) versions of a system are deployed for a certain period of time and users either interact with one or the other version (Jannach and Jugovac, 2019). Although these tests are often complex to execute and require significant effort, the main advantage is that they are able to directly measure business KPIs (e.g., revenue, profit) (Chen, 2017) and to compare different algorithms in production.

<sup>11</sup> We discuss the most frequently used offline metrics in Section 5.2.

**Table 8**

Most frequently used offline evaluation metrics in the surveyed literature.

Refs	Metric	Type	Definition
Gunawardana et al. (2022)	$Prec@k = \frac{1}{ U } \sum_{u \in U} \frac{\sum_{j=1}^k rel_{u,j}^y}{k}$	(19) Relevance	<i>Precision</i> at position $k$ is the number of relevant items in the top- $k$ recommendations over the number of recommended ones.
Gunawardana et al. (2022)	$Rec@k = \frac{1}{ U } \sum_{u \in U} \frac{\sum_{j=1}^k rel_{u,j}^y}{\sum_{j=1}^n x_{u,j}}$	(20) Relevance	<i>Recall</i> at position $k$ is the number of relevant items in the top- $k$ recommendations over the total number of relevant ones.
Gunawardana et al. (2022)	$HR@k = \frac{1}{ U } \sum_{u \in U} \begin{cases} 1 & \text{if } \sum_{j=1}^k rel_{u,j}^y \geq 1 \\ 0 & \text{otherwise} \end{cases}$	(21) Relevance	<i>Hit-Rate</i> at position $k$ is the fraction of users for which the recommendations list contains at least one relevant item.
Gunawardana et al. (2022)	$MRR@k = \frac{1}{ U } \sum_{u \in U} \frac{1}{j_u^1}$	(22) Relevance	<i>Mean Reciprocal Rank</i> at position $k$ is the mean rank of the first relevant item in the recommendations list. In the equation, $j_u^1$ is the rank (position) of the first item relevant to user $u$ .
Gunawardana et al. (2022)	$NDCG@k = \frac{1}{ U } \sum_{u \in U} \frac{\sum_{j=1}^k \frac{rel_{u,j}^y}{\log_2(j+1)}}{IDCG_u@k}$	(23) Relevance	<i>Normalized Discounted Cumulative Gain</i> at position $k$ is the inverse log reward on all positions with relevant items among the top- $k$ recommended ones. In the equation, $IDCG_u@k$ is the <i>Ideal Discounted Cumulative Gain</i> obtained by sorting all the items relevant to the user in descending order.
Malthouse et al. (2019b) <sup>a</sup>	$Revenue@k = \sum_{u \in U} \sum_{j=1}^k rel_{u,j}^y \cdot p_j$	(24) Value	<i>Revenue</i> at position $k$ is the revenue from relevant items in the recommendations list.
Jannach and Adomavicius (2017) <sup>a</sup>	$Profit@k = \sum_{u \in U} \sum_{j=1}^k rel_{u,j}^y \cdot v_j$	(25) Value	<i>Profit</i> at position $k$ is the profit from relevant items in the recommendations list.
Cai and Zhu (2019) <sup>a</sup>	$EP@k = \sum_{u \in U} \sum_{j=1}^k \hat{x}_{u,j}(\Theta) \cdot v_j$	(26) Value	<i>Expected Profit</i> at position $k$ is the statistical profit it is expected to achieve by the recommendations considering the expected user interest $\hat{x}_{u,j}(\Theta)$ . $EP@k$ is referred to as statistical profit (compared with $Profit@k$ in Eq. (25)), because the probability that the user accepts the recommendations instead of the actual ground truth relevance information is considered.
Kompan et al. (2022) <sup>b</sup>	$PAH@k = \frac{1}{ U } \cdot \frac{Profit@k}{Volume@k}$	(27) Value	<i>Profit-at-Hit</i> at position $k$ is the average profit per user from relevant items in the recommendations list.
Louca et al. (2019) <sup>a</sup>	$P\text{-}NDCG@k = \frac{1}{ U } \sum_{u \in U} \frac{\sum_{j=1}^k \frac{rel_{u,j}^y \cdot p_j}{\log_2(j+1)}}{P\text{-}IDCG_u@k}$	(28) Value	<i>Price-Based Normalized Discounted Cumulative Gain</i> at position $k$ is defined as $NDCG@k$ , where the gain is given by the items price. In the equation, $P\text{-}IDCG_u@k$ is the <i>Price-Based Ideal Discounted Cumulative Gain</i> obtained by sorting the prices of all relevant items to the user in descending order.

<sup>a</sup> Note that for the sake of notation we used  $p_j$  and  $v_j$  as variables to indicate the price and profit of the recommended item at position  $j$ , but these variables depend only on the item and not on the position.

<sup>b</sup> The formulas capture the main essence of the metrics.

These tests are used many times in the surveyed literature.<sup>12</sup> since algorithms are often designed to optimize such KPIs. For example, A/B tests are used to measure the effects of a profit-aware algorithm deployed on Alibaba's AliOS appstore (Zhang et al., 2017b) and the CTR of a reinforcement learning-based algorithm deployed on a large e-commerce platform (Pei et al., 2019).

## 5.2. Metrics used in offline evaluations

A variety of metrics are used in the literature in offline evaluations, including both accuracy metrics to assess the relevance prediction performance as well as metrics aimed to investigate organizational value.

Given  $rel_{u,j}^y$  as a ground truth relevance<sup>13</sup> variable that indicates whether the item recommended at position  $j$  in the ordered ranking  $\mathcal{Y}_{u,k}$  is relevant or not for user  $u$ , we report in Table 8 the metrics used for offline evaluations in the literature. In the table we indicate

for each metric the reference, the formula, the type, as well as its definition. In the following, we mainly focus on value metrics, since relevance prediction metrics (e.g., Precision, Hit-Rate, NDCG — see Eqs. (19), (21), (23)), are already widely known (Gunawardana et al., 2022) and do not require further discussion here.

The general principle is the same for all value metrics. Similarly to relevance prediction metrics, first a list of top- $k$  recommendations is generated for each user. Then the recommendations are compared to the ground truth and certain value-related aspects are collected. Those value-related aspects are connected to the price and profit (and in more general terms also to the utility) of each recommended item. In particular, differently from prediction relevance metrics, value ones do not only count the hits but multiply that hit by the items' price and profit. We briefly introduce the most frequently used value metrics as follows:

- *Revenue@k* (Eq. (24)) (Malthouse et al., 2019a,b; Azaria et al., 2013) indicates the total revenue from the sale of recommended products actually purchased by users;
- *Profit@k* (Eq. (25)) (Jannach and Adomavicius, 2017; Ghanem et al., 2022; Concha-Carrasco et al., 2023; Nemati and Khademolhosseini, 2020) indicates the total profit from the sale of recommended products actually purchased by users;

<sup>12</sup> We discuss results of A/B tests in Section 5.3.

<sup>13</sup> The relevance of each item typically corresponds to the value of the ground truth  $x_{u,i} \in \{0,1\}$ , i.e., assuming  $x_{u,i} = 1$  if the item was actually purchased by the user, and  $x_{u,i} = 0$  if not.

- $EP@k$  (Eq. (26)) (Cai and Zhu, 2019) indicates the *statistical* expected profit from the recommendation.  $EP@k$  compared to  $Profit@k$  is referred to as statistical because the probability of the user accepting the recommendations is considered rather than the ground truth information;
- $PAH@k$  (Eq. (27)) (Kompan et al., 2022) indicates the overall profit generated by the recommendation per user divided by the number of items sold;
- $P\text{-}NDCG@k$  (Eq. (28)) (Louca et al., 2019; Lin et al., 2019) indicates the total revenue generated on average per user from the recommendation compared to the theoretically achievable maximum revenue.  $P\text{-}NDCG@k$ , like  $NDCG@k$  (Eq. (23)) (Gunawardana et al., 2022), gives more importance to the higher-priced items positioned on the top of the ranking.<sup>14</sup>

However, analyzing the surveyed articles, some open issues can be identified. In particular, we observe that the literature is mostly scattered, application-specific, and there are no well-defined standards in offline assessment of business value (Jannach and Adomavicius, 2017; De Biasio et al., 2023b). Often the same metric is referred to by different names (e.g., *Price-Based NDCG* (Louca et al., 2019), vs. *G-DCG* (Lin et al., 2019)). Other times, researchers report results that are not comparable to each other because application-specific metrics are proposed in the article to investigate certain types of value (e.g., perishability (Seymen et al., 2022), marginal utility per dollar (Ge et al., 2019)). In fact, under certain circumstances, it would not even be possible to use certain metrics. For example, in the case where the underlying dataset carries only price information and not profit information (e.g., Amazon (Ni et al., 2019), Tmall (Zhu et al., 2018)), the metrics related to the latter would not be computable without using synthetic profit distributions of the dataset.<sup>15</sup> Finally, in cases where simulations are used, the calculation of value metrics may be based on assumptions. The main assumption that can be found (Jannach and Adomavicius, 2017; Ghanem et al., 2022) is that in some studies the user is supposed to always buy at least one item of the top- $k$  recommended ones. In these cases, since the user may not have actually purchased any of the recommended items if his or her purchase history is analyzed, the underlying ground truth information may be unrealistic.

### 5.3. Real-world A/B tests and user studies

Many authors evaluate the performance of ECRSs algorithms using A/B tests or user studies. As is known in the literature, offline evaluation results are not necessarily a valid indicator of online performance (Jannach and Jugovac, 2019; Jannach and Hegelich, 2009). This is often due to the fact that different metrics are used for the two types of experimental evaluation (Dias et al., 2008; Senecal and Nantel, 2004). While offline metrics are often used to measure relevance prediction accuracy (e.g., Precision, NDCG), online metrics are used instead to measure business value (e.g., CTR, GMV, Revenue) (Kirshenbaum et al., 2012; Garcin et al., 2014). Companies are usually much more interested in assessing how algorithms impact real-world business KPIs exploiting online metrics.

In Table 9 we list the studies in the surveyed literature that measure the performance of the proposed systems through A/B tests or user studies. In Table 10 we then briefly summarize the meaning of each online metric that is considered for the analysis<sup>16</sup> (i.e., IPV, CTR, CVR,

GMV, Revenue, Profit). We refer readers to a recent survey (Jannach and Jugovac, 2019) on this topic for further insights into online metrics.

Analyzing Table 9 we can make some interesting observations. Some considerations depend on the nature of the particular evaluation methodology (i.e., A/B test vs. user study). For example, considering the recommendations channel and the number of subjects, we note that user studies typically involve few users recruited through e-mail campaigns (Panniello et al., 2016b; Zhu et al., 2014) or Amazon Mechanical Turk (Azaria et al., 2013; Zhao et al., 2015). Instead, A/B tests are typically performed on a large scale, exploiting existing systems with large customer bases (Zhang et al., 2017b; Pei et al., 2019), some of well-known brands (e.g., Walmart, Taobao, Alibaba, NetEase) (Maragheh et al., 2022; Zhang et al., 2017b; Deng et al., 2020; Ji et al., 2021). Moreover, from a performance point of view, all the studies, whether they are based on user studies or A/B tests, show that ECRSs are able to potentially bring huge business value to the firm. In fact, increases in online metrics are reported in all studies. In some cases, the authors report significant performance improvements<sup>17</sup> (e.g., +48.92% CVR (Zhu et al., 2014), +35% revenue (Agarwal et al., 2022), +32% profit (Zhang et al., 2017b)).

However, there may be some limitations regarding the insights we can get from the studies. For example, most of the A/B tests last a very short time, i.e., less than three weeks<sup>18</sup> (Cavenaghi et al., 2022; Li et al., 2021; Ji et al., 2021; Pei et al., 2019; Lin et al., 2019; Zhang et al., 2017b; Zhao et al., 2015; Zhu et al., 2014; Azaria et al., 2013). In some cases, the baselines are proprietary algorithms and their internal mechanisms are unknown (Maragheh et al., 2022; Cavenaghi et al., 2022; Deng et al., 2020; Azaria et al., 2013) (e.g., Walmart Ranker). In other cases, results depend on assumptions. For example, a study (Zhao et al., 2015) based on Amazon Mechanical Turk uses synthetic profit information, as the authors did not have product costs available. Another study (Panniello et al., 2016b) uses some proxies for offline purchases in addition to explicit purchase data from the firm's online site to measure revenue. In that specific context, offline purchases cannot be connected to the online identities of experiment participants. In particular, the authors treated items that received high ratings by users after they clicked on the "see more details" link as purchases to calculate profit.

### 5.4. Available datasets

Analyzing the ECRSs literature, our survey reveals that many studies report results based on proprietary datasets. This is mainly due to the fact that certain types of information (e.g., prices, profits, purchases, demographics) are of strategic importance to companies, and uncontrolled sharing could create significant economic damage. For example, some information is sensitive to the user, and non-anonymized sharing could have major legal implications due to privacy laws, as well as significant impact on brand reputation. In addition, competitors could make use of economic data related to purchasing and profitability to study weaknesses in the business model and take away market share. However, especially recently, several studies also report results based on public datasets.

<sup>17</sup> To ensure evaluation reliability, many authors test the proposed algorithm in different configuration environments reporting different results for each of them (Li et al., 2021). In these cases, Table 9 shows a range instead of a single value in metrics improvement.

<sup>18</sup> Performing long-term A/B tests on a real platform is complex (Jannach and Jugovac, 2019) and significant effort is required both in the planning and analysis phases. Often the test could cause financial damage to the brand as users could lose trust in the company due to ineffective recommendations. Other times, it is necessary to re-run the test because of bugs. Or again, certain events (e.g., Easter, Super Bowl) or global macroeconomic circumstances (e.g., 2020 COVID-19 crisis, 2022 Ukrainian war) may impact performance.

<sup>14</sup> Note that, as in IR (Kobayashi and Takeda, 2000; Bellogin and Said, 2019), value metrics can be rank-agnostic (e.g., *Revenue@k*, *Profit@k*) or rank-aware (e.g. *P-NDCG@k*), depending on whether the position of the recommended items in the ranking is considered for evaluation or not.

<sup>15</sup> We discuss the synthetic profit issue in Section 5.4.

<sup>16</sup> Some niche metrics used to measure certain application-specific factors reported in the studies are not considered.



**Table 9**

Results of real-world A/B tests and user studies in the surveyed literature. In the table we report: the channel used to convey the recommendations; the number of subjects (i.e., users, searches, or sessions); the overall duration of the study (e.g. 20 days, 1 year); the baseline against which the proposed algorithm in the study is compared; and the relative improvements in online metrics of the proposed algorithm compared to the baseline.

Ref	Year	Eval.	Channel	Subjects	Durat.	Baseline	$\Delta\%$ IPV	$\Delta\%$ CTR	$\Delta\%$ CVR	$\Delta\%$ GMV	$\Delta\%$ Rev.	$\Delta\%$ Prof.
Maragheh et al. (2022)	2022	A/B Test	E-Commerce Platform (Walmart)	36M sessions	–	Walmart Ranker				+0.71%		
Cavenaghi et al. (2022)	2022	A/B Test	Booking Platform	1M searches	20 days	Platform Ranker		[–0.50%, +2.00%]				
Agarwal et al. (2022)	2022	A/B Test	E-Commerce Platform	–	–	Co-Purchase					+35.0%	
Li et al. (2021)	2021	A/B Test	Online Insurance Platform	–	1 week	LogReg			+1.05%, 3.98%		+2.7%, 16.2%	
Ji et al. (2021)	2021	A/B Test	E-Commerce Platform (Taobao)	–	1 week	Vanilla-CTR	+6.25%, 8.67%			+12.31%, 18.03%		
Deng et al. (2020)	2020	A/B Test	Video Game Platform (NetEase)	–	1 year	Platform Ranker			+60.0%	+15.0%		
Pei et al. (2019)	2019	A/B Test	E-Commerce Platform	1M users	1 week	Item KNN	+8.80%	+8.20%		+27.90%		
Lin et al. (2019)	2019	A/B Test	E-Commerce Platform	–	3 days	LETORIF	+23.76%	+13.80%		+3.62%		
Zhang et al. (2017b)	2017b	A/B Test	Appstore (Alibaba AliOS)	1M users	2 weeks	LinDP			–6.00%			+32.0%
Panniello et al. (2016b) <sup>a</sup>	2016b	User Study	Mail Campaign	260 users	9 weeks	CBF					+94.39%	+137%
Zhao et al. (2015)	2015	User Study	Amazon Mechanical Turk	79 users	–	Amazon Price						+241%, 248%
Zhu et al. (2014)	2014	User Study	Mail Campaign	few users	1 week	Markov Model		+7.43%	+48.92%			
Azaria et al. (2013)	2013	User Study	Amazon Mechanical Turk	245 users	–	Pers. NonCF					+28.57%	

<sup>a</sup> The relative improvements are determined by analyzing the sentence “Overall revenue generated during the experiment was €428 for the content-based group, €832 for the profit-based group” and Figure 11b in the original paper (Panniello et al., 2016b).

**Table 10**

Most frequently used online metrics in the surveyed literature (Jannach and Jugovac, 2019).

Metric	Meaning
IPV	<i>Individual Page View</i> is the overall number of clicked items on the platform.
CTR	<i>Click-Through Rate</i> is the number of user clicks divided by the number of items shown.
CVR	<i>Click-Conversion Rate</i> is the number of purchases (or other events) divided by the number of clicks.
GMV <sup>a</sup>	<i>Gross Merchandise Value</i> is the number of items sold multiplied by their price.
Revenue <sup>a</sup>	<i>Revenue</i> is equal to GMV minus any commissions from item sellers.
Profit <sup>b</sup>	<i>Profit</i> is equal to Revenue minus any item costs.

<sup>a</sup> GMV and Revenue almost always indicate the same measure except in B2C marketplaces like eBay.

<sup>b</sup> Depending on the type of subtracted cost (e.g., raw materials, marketing), profit can be gross, net, or have additional nuances (e.g., EBITDA, EBIT).

In Table 11 we report the most frequently used public datasets in the surveyed literature. Specifically, in addition to statistical information such as the number of users, items, interactions, and the density of the dataset, we also report the type of event/interaction (e.g., click, add-to-cart, purchase, rating), and the presence of relevant features for ECRSs algorithms, i.e., date, user demographics, product category, price, and profit.

Analyzing the reported information, we can make some observations. First, both the datasets’ density and size, i.e., the number of

interactions, vary greatly. Some of them are quite sparse (e.g., REC-RL (Pei et al., 2019)), whereas others are dense (e.g., Jester (Goldberg et al., 2001)). Some are quite small (e.g., Foodmart (Corporation, 1998)), while others are large (e.g., Amazon (Ni et al., 2019)). In addition, as expected, most of the datasets contain economic information related to actual purchases, as well as prices and possibly profit of products (e.g., in the Cosmetics (Anon, 2019), Diginet-ica (CIKM 2016 Cup, 2016), Ta-Feng (Hsu et al., 2004), and Tmall (Zhu et al., 2018) datasets). Indeed, as discussed earlier, economic information is typically used for both algorithmic and evaluation purposes. However, as can be noted, some datasets do not contain prices (e.g., MovieLens (Harper and Konstan, 2016), Netflix Prize (Bennett et al., 2007), Book-Crossing (Ziegler et al., 2005), Epinions (Richardson and Domingos, 2002), Last.fm (McFee et al., 2012)) and currently only Foodmart (Corporation, 1998) contains profit. We observe that those datasets are the most frequently used in RSs research. In particular, although profit is very important especially to train profit-aware models, we note various studies (Jannach and Adomavicius, 2017; Ghanem et al., 2022; Brand, 2005; Akoglu and Faloutsos, 2010; Piton et al., 2011; Lu et al., 2014; Cai and Zhu, 2019; Nemati and Khademolhosseini, 2020; Concha-Carrasco et al., 2023) assuming some synthetic profit distribution, e.g., normal (Ghanem et al., 2022), or random (Nemati and Khademolhosseini, 2020). This assumption would allow to overcome the profit availability issue. However, as reported in almost all the studies, this also constitutes an important limitation. In fact, under real circumstances, the profit distribution could be very different from the synthetic one used for the experiments, and the results could vary considerably.

**Table 11**

Most used datasets in the surveyed literature.

Ref	Dataset	#User	#Item	#Inter	Density	Event	Date	Dem.	Cat.	Price	Prof.
Anon (2019)	Cosmetics	$1.64 \times 10^6$	$5.46 \times 10^4$	$2.07 \times 10^7$	0.023%	View, Add-to-Cart, Remove-From-Cart, Purchase	✓		✓	✓	
CIKM 2016 Cup (2016)	Diginetica	$2.05 \times 10^5$	$1.84 \times 10^5$	$9.93 \times 10^5$	0.002%	Query, Click, Purchase	✓		✓	✓	
Ni et al. (2019)	Amazon(2018) <sup>a</sup>	–	$1.55 \times 10^7$	$2.33 \times 10^8$	–	Review, Ratings	✓		✓	✓	
Zhang et al. (2015)	Yelp(Full) <sup>a</sup>	$5.56 \times 10^6$	$5.39 \times 10^5$	$2.89 \times 10^8$	0.009%	Review, Ratings	✓		✓	✓	
Dror et al. (2012)	Yahoo!Music	$1.95 \times 10^6$	$9.82 \times 10^4$	$1.16 \times 10^7$	0.006%	Ratings					
Hsu et al. (2004)	Ta-Feng	$3.23 \times 10^4$	$2.38 \times 10^4$	$8.18 \times 10^5$	0.106%	Purchase	✓	✓	✓	✓	
Harper and Konstan (2016)	MovieLens(20M) <sup>a</sup>	$1.38 \times 10^5$	$2.73 \times 10^4$	$2.00 \times 10^7$	0.529%	Ratings	✓	✓	✓		
Bennett et al. (2007)	NetflixPrize	$4.80 \times 10^5$	$1.78 \times 10^4$	$1.00 \times 10^8$	1.177%	Ratings	✓				
Fournier-Viger et al. (2016)	SPMF	–	$1.65 \times 10^4$	$8.82 \times 10^4$	–	Purchase	✓			✓	
Lin et al. (2019)	EC-REC	–	–	–	–	View, Click, Purchase	✓			✓	
Ziegler et al. (2005)	Book-Crossing	$1.05 \times 10^5$	$3.41 \times 10^5$	$1.15 \times 10^6$	0.003%	Ratings		✓			
Corporation (1998)	Foodmart	$8.84 \times 10^3$	$1.56 \times 10^3$	$2.61 \times 10^5$	1.894%	Purchase	✓	✓	✓	✓	✓
McFee et al. (2012)	Last.fm	$1.89 \times 10^3$	$1.76 \times 10^5$	$9.28 \times 10^4$	0.027%	Listen	✓		✓		
Richardson and Domingos (2002)	Epinions	$2.27 \times 10^5$	$2.32 \times 10^5$	$1.13 \times 10^6$	0.002%	Ratings, Graph	✓				
Goldberg et al. (2001)	Jester	$7.34 \times 10^4$	$1.01 \times 10^2$	$4.14 \times 10^6$	55.779%	Ratings					
Pathak et al. (2017)	Steam	$2.57 \times 10^6$	$3.21 \times 10^4$	$7.79 \times 10^6$	0.009%	Purchase	✓		✓	✓	
Zhu et al. (2018)	Tmall	$9.64 \times 10^5$	$2.35 \times 10^6$	$4.45 \times 10^7$	0.001%	View, Add-to-Cart, Add-to-Wishlist, Purchase	✓		✓		
Pei et al. (2019)	REC-RL	$4.90 \times 10^7$	$2.00 \times 10^8$	$7.63 \times 10^8$	$7.79 \times 10^{-6}\%$	Click, Add-to-Cart, Add-to-Wishlist, Purchase	✓			✓	
Ventatesan (2007)	Dunnhumby	$2.50 \times 10^3$	$9.24 \times 10^4$	$2.60 \times 10^6$	1.125%	Purchase	✓	✓	✓	✓	
Pisharath (2005)	Chainstore	–	$4.61 \times 10^4$	$1.11 \times 10^6$	–	Purchase				✓	
Anon (2018)	NetEase	$1.85 \times 10^4$	$1.24 \times 10^5$	$1.13 \times 10^6$	0.049%	Playlist					

<sup>a</sup> Since there may be multiple versions of the same dataset, we report the statistics of the most recent one.**Table 12**

Studies in the surveyed literature that provide the code.

Ref	Year	Dimension	Link
Chang et al. (2023)	2023	Promotional	<a href="https://github.com/cjx0525/BGCN">https://github.com/cjx0525/BGCN</a>
Zhang et al. (2022b)	2022b	Price-sensitivity	<a href="https://github.com/Zhang-xiaokun/CoHNN">https://github.com/Zhang-xiaokun/CoHNN</a>
Wu et al. (2022)	2022	Price-sensitivity	<a href="https://github.com/PCNet-Code">https://github.com/PCNet-Code</a>
Ghanem et al. (2022)	2022	Profit-awareness	<a href="https://github.com/nadaa/rec-strategies-abm">https://github.com/nadaa/rec-strategies-abm</a>
Avny Brosh et al. (2022)	2022	Promotional	<a href="https://github.com/tzoof/BRUCE">https://github.com/tzoof/BRUCE</a>
Agarwal et al. (2022)	2022	Promotional	<a href="https://github.com/muhanzhang/SEAL">https://github.com/muhanzhang/SEAL</a>
Zhan et al. (2021)	2021	Long-term value sustainability	<a href="https://github.com/google-research/google-research/tree/master/recs_ecosystem_creator_rl">https://github.com/google-research/google-research/tree/master/recs_ecosystem_creator_rl</a>
Zheng et al. (2020)	2020	Price-sensitivity	<a href="https://github.com/DavyMorgan/ICDE20-PUP">https://github.com/DavyMorgan/ICDE20-PUP</a>
Xu et al. (2020)	2020	Economic utility modeling	<a href="https://github.com/zhichaoxu-shufe/E-commerce-Rec-with-WEU">https://github.com/zhichaoxu-shufe/E-commerce-Rec-with-WEU</a>
Ge et al. (2020)	2020	Economic utility modeling	<a href="https://github.com/TobyGE/Risk-Aware-Recommendation-Model">https://github.com/TobyGE/Risk-Aware-Recommendation-Model</a>
Dai et al. (2020)	2020	Economic utility modeling	<a href="https://github.com/xydaisjtu/U-rank">https://github.com/xydaisjtu/U-rank</a>
Chang et al. (2020)	2020	Promotional	<a href="https://github.com/cjx0525/BGCN">https://github.com/cjx0525/BGCN</a>
Pei et al. (2019)	2019	Long-term value sustainability	<a href="https://github.com/rec-agent/rec-rl">https://github.com/rec-agent/rec-rl</a>
Lin et al. (2019)	2019	Profit-awareness	<a href="https://github.com/weberrr/PE-LTR">https://github.com/weberrr/PE-LTR</a>
Ge et al. (2019)	2019	Economic utility modeling	<a href="https://github.com/TobyGE/Maximizing-Marginal-Utility-per-Dollar-for-Economic-Recommendation">https://github.com/TobyGE/Maximizing-Marginal-Utility-per-Dollar-for-Economic-Recommendation</a>

### 5.5. Reproducibility maturity

The impact of reproducibility on the progress of science is undeniable. However, although there has generally been an increase in reproducible papers in AI over the years (Gundersen and Kjensmo, 2018), many of them are still not sufficiently well documented to reproduce the results of the reported experiments (Haibe-Kains et al., 2020). This problem is observed several times in the field of RSs (Beel et al., 2016; Cremonesi and Jannach, 2021), with well-known cases regarding articles that proposed neural algorithms (Rendle et al., 2020; Ferrari Dacrema et al., 2019), highlighting for example: non-uniform and lax standards in adopting the correct experimental evaluation methodologies (Sun et al., 2020); questionable choices on the use and fine-tuning of baselines for comparative experiments (Ferrari Dacrema et al., 2021).

In particular, by reviewing the ECRSs literature, we note several limitations concerning the reproducibility of the studies. As reported in

Table 12, only a very small subset of 15 articles, out of 135 (11.11%) identified by the present systematic review share the implementation code.<sup>19</sup> Notably, as can be seen from the table, we find no article that publicly share the code prior to 2019. In addition, the level of reproducibility is quite uneven when considering the different subdomains of ECRSs. In particular, we note the following critical issues: there are many articles published in the *profit-awareness* subdomain but only two of them share the code; all the articles published in the field of *promotional* strategies refer to relevance-based bundling methods (i.e., there is no code shared about brand-awareness and pricing methods); the code of articles concerning *price-sensitivity* and *long-term value* methods is published only for the most recent and advanced

<sup>19</sup> We did not dive into the code details because even if the code is shared, it was found earlier in the RSs literature (Sun et al., 2020; Ferrari Dacrema et al., 2021; Cremonesi and Jannach, 2021) that in many cases important information is missing to ensure reproducibility (e.g., pre-processing code).

GNN- and RL-based algorithms. Consequently, it would be beneficial and significantly accelerate progress in this field if researchers would pay special attention to increasing the level of reproducibility.

## 6. Current challenges and future research

In this section we discuss current challenges of ECRSs and possible future research directions.

*Comparing different algorithmic approaches.* A multitude of algorithmic approaches for optimizing business value are proposed in the literature. In this paper, we categorize them at a high level into in-processing and post-processing methods (De Biasio et al., 2023b) considering five DAs. However, most of the approaches are never compared with each other and may have specificities that may make them preferable in certain circumstances over others. For example, no study has yet compared in-processing with post-processing approaches. In addition, different types of in-processing algorithms are found in the literature. In particular, it is proposed for example to extend the objective function of MF (Ge et al., 2014; Chen et al., 2014, 2017; Sato et al., 2015), or to use GNNs (Zheng et al., 2020, 2021; Zhang et al., 2022b) to generate price-sensitive recommendations. Moreover, value neighbor selection (Cai and Zhu, 2019), graph-based (Brand, 2005; Akoglu and Faloutsos, 2010; Qu et al., 2014) or evolutionary (Nemati and Khademolhosseini, 2020; Concha-Carrasco et al., 2023) profit-aware algorithms are proposed as well. However, some types of methods are applied only to certain DAs. For example, although feasible in practice, no profit-aware MF objective function extensions or GNNs were surfaced through our study. Similarly, no neighbor selection or evolutionary price-sensitive algorithm was found so far. Therefore, it might be useful for the future both to compare in-processing and post-processing approaches and to implement theoretically feasible algorithms not yet found in the literature, comparing them with existing ones.

*Optimizing business value trade-offs.* Business value optimization is complex, and the systems must consider multiple trade-offs (Jannach and Adomavicius, 2017; De Biasio et al., 2023b) in the optimization process. For example, considering real-world businesses based on an advertising revenue model (e.g., YouTube, Alibaba's AliOS), it is very important to find the right balance between the ad revenue generated by sponsored items and the actual interests of the user (Zhang et al., 2017b; Malthouse et al., 2019b). In particular, special care must be taken not to compromise user trust (Panniello et al., 2016b; Hosanagar, 2008). In fact, it is shown both through simulations (Ghanem et al., 2022), in user studies (Nilashi et al., 2016) and subsequent A/B tests (Panniello et al., 2016b) that trust is positively correlated with propensity to purchase. A system that is too biased toward higher-value items that provides irrelevant recommendations to the user (Jannach and Adomavicius, 2017; De Biasio et al., 2023b) could risk impacting the organization's reputation and driving away customers. To address this issue various studies (Azaria et al., 2013; Wang and Wu, 2009; Lu et al., 2014; Malthouse et al., 2019b; Zhang et al., 2017b; Kompan et al., 2022) propose algorithms with the goal of balancing the interests of multiple stakeholders (Abdollahpouri et al., 2020; Abdollahpouri and Burke, 2022), particularly considering the profitability/relevance trade-off (Jannach and Adomavicius, 2017), and optimizing short- or long-term value (Hosein et al., 2019). Furthermore, as various studies pointed out, algorithms should take care also of explainability (Zhang and Chen, 2020; Tintarev and Masthoff, 2007; Montagna et al., 2023), fairness (Zehlike et al., 2023a,b; Patro et al., 2022; Pitoura et al., 2022), and diversity (Kunaver and Požrl, 2017; Panniello et al., 2016b) since they are directly related to trust (Deng et al., 2020). However, the current literature has not thoroughly investigated the impact of many of these factors on business value. Hence, providing efficient algorithms to simultaneously optimize multiple business value trade-offs (e.g., profit, fairness, and trust) could be a valuable research direction for the future.

*Comprehensive purpose-oriented offline and online evaluation.* Evaluating ECRSs often requires the use of methods that are different from those used for traditional RSs (Zhao et al., 2023; Chen, 2017). As a result, there are still many open challenges in order to be able to evaluate ECRSs in a comprehensive, purpose-oriented way (Jannach and Adomavicius, 2016; Alslaity and Tran, 2021) (i.e., that considers the purposes for which the system is designed). Several of these challenges follow from the analysis presented in this paper. For example, in offline evaluation, it is necessary to use business value metrics besides the widely adopted relevance prediction metrics (Gunawardana et al., 2022). Studies often exploit a variety of metrics (Guo et al., 2020; Cai and Zhu, 2019; Jannach and Adomavicius, 2017; Kompan et al., 2022; Louca et al., 2019) albeit with similar objectives, and the results reported are not comparable with each other. In addition, offline evaluation methodologies are not standardized and often are designed ad-hoc according to specific needs (Hosanagar, 2008). Moreover, besides a few exceptions (Ge et al., 2019; Ghanem et al., 2022; Zhang et al., 2022b; Zhan et al., 2021; Pei et al., 2019; Xu et al., 2020; Lin et al., 2019), most studies are difficult to reproduce and are often based on proprietary datasets or public datasets with synthetic data (Nemati and Khademolhosseini, 2020; Concha-Carrasco et al., 2023). In fact, most datasets (Harper and Konstan, 2016; Bennett et al., 2007; Anon, 2019; Ni et al., 2019; Hsu et al., 2004; Richardson and Domingos, 2002; Ziegler et al., 2005) do not contain information such as profitability (Corporation, 1998), which is however needed for model training. Regarding A/B tests on the other hand, many of them last for a short time (Li et al., 2021; Pei et al., 2019; Lin et al., 2019) and involve a small set of users (Zhu et al., 2014; Azaria et al., 2013; Zhao et al., 2015; Panniello et al., 2016b) to avoid potential economic risks (Jannach and Jugovac, 2019; Panniello et al., 2016b) for the organization hosting the test. Hence, there could be several future research directions in the field of evaluation. For example, it is necessary to develop better offline value metrics that are indicative of online performance in a given (prototype) scenario. In addition, large-scale A/B tests (i.e., involving many users) and reproducibility studies are also required.

*Design of holistic algorithmic methods.* In this work, decomposing the literature on ECRSs into five different DAs, various algorithmic approaches for optimizing business value are explored. However, most of the existing methods (Chen et al., 2008; Pei et al., 2019; Chen et al., 2017; Ge et al., 2019; Zhao et al., 2015) focus exclusively on one of the five perspectives. There are a few exceptions (Kompan et al., 2022; Maragheh et al., 2022) that involve more than one DA that study, for example (Kompan et al., 2022), how to combine price-sensitivity with profit-awareness to generate more profit while keeping relevance high. A very small subset of studies (Demirezen and Kumar, 2016; Seymen et al., 2022; Ettl et al., 2020), on the other hand, provide broader reasoning by also discussing inventory management techniques that might be useful for analogous purposes. Currently, the literature lacks holistic methods capable of leveraging multiple approaches simultaneously (De Biasio et al., 2023b; Jannach and Adomavicius, 2017) complementing each other to optimize different nuances of business value (Jannach and Jugovac, 2019) while also considering the inter-relationship (He et al., 2022) between them. In addition, it is also necessary to consider the relationship between sales and marketing processes with operational (Seymen et al., 2022; Demirezen and Kumar, 2016; Ettl et al., 2020) and financial processes so as to propose methods for improving the entire business ecosystem, e.g., reducing raw material costs, minimizing logistics delays, or optimizing cash flows.

## 7. Conclusion and implications

In this paper, we review the existing literature on ECRSs. Unlike traditional RSs, economic ones aim to directly optimize profitability by exploiting purchase information (e.g., price and profit) and related

concepts from economics and marketing. This topic is highly important because organizations aim to optimize (long-term) profit. Accordingly, ECRSs are well-suited for use in commercial applications such as e-commerces, media streaming sites, and advertising platforms, as they offer various benefits for organizations to increase their business KPIs. In this survey, we identify a number of relevant works addressing a multitude of related issues on ECRSs. In particular, although the literature is highly scattered, five different approaches that jointly consider the interests of customers and organizations are identified in this paper (e.g., price sensitivity, profit awareness).

At present, the application of a certain approach in any company can be viewed as a strategic management decision. Indeed, while all approaches are useful (and can hypothetically be applied at the same time) for increasing corporate profitability, some may be more effective than others in a specific business context. The management should make wise decisions about which approach to employ by considering, for example, the company's particular business strategy and revenue model, the expected business value returns and the potential behavioral harms that could arise from an inappropriate use of a particular approach. For example, if the platform is in its early stages and does not have many customers, promotional (and especially brand-awareness) approaches can help increase platform adoption and gain a large customer base. Conversely, if the platform already has many customers, profit-awareness (and particularly long-term value sustainability) approaches can boost corporate profitability. Similarly, if many customers are leaving the platform, the business may employ utilitarian or promotional approaches to increase retention and build customer loyalty. In addition, price-sensitivity methods may be useful in cases where price is an important driver in the user's final choice. However, the company should consider to balance price-sensitivity appropriately with profit-awareness to avoid recommending unprofitable items.

Much work has been done on RSs since their first formulation and many different approaches were proposed over the years. However, even if these systems were originally built to support business decisions, not much literature has yet focused on designing ECRSs to directly optimize organizational profitability. This review shall help academic scholars and industry partners to navigate the existing literature and understand the state-of-the-art. We hope this work will serve as a valuable starting point to foster future research and shift academic efforts towards more impactful RSs research that matters (Jannach and Adomavicius, 2016; Jannach and Bauer, 2020).

## CRedit authorship contribution statement

**Alvise De Biasio:** Conceptualization, Methodology, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Nicolò Navarin:** Writing – review & editing. **Dietmar Jannach:** Conceptualization, Methodology, Validation, Resources, Writing – original draft, Writing – review & editing, Supervision.

## 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.

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