Recommender systems: A systematic literature review, synthesis and framework for future capabilities

Srishti Bokadia | Ruchi Jain | Rushina Singhi

Abstract This study offers a comprehensive exploration of recommender systems (RSs) with a focus on their influence on consumers’ purchase intentions in the realm of e-commerce. Employing the Scientific Procedures and Rationales for Systematic Literature Reviews (SPAR-4-SLR) method, the authors identified and evaluated 908 high-quality papers to systematically categorize RS. This paper outlines these categories and reviews major developments within them, identifying significant constructs influencing consumer purchasing decisions. The outcome is a conceptual framework illustrating the interrelationships among these constructs, providing a novel contribution to the literature. This framework lays the groundwork for future studies in the field and provides valuable insights for marketing professionals seeking to develop RS-based strategies.

Keywords: recommender systems, artificial intelligence, e-commerce, influence on consumer, purchase intention, consumer profile

1. Introduction

In the contemporary digital landscape, online services have offered ease in retrieving any extensive amount of online information. Substantial data about different products and services are available on the web. Additionally, users can post reviews, comments and ratings about them (Roy & Dutta, 2022). Sometimes, this deluge of data can make it difficult for the user to find the right information to help them make informed decisions. Amidst this data overload, individualized and personalized suggestions are pivotal in assisting users in decision-making processes (Monti et al., 2021). This consequently helps the user select the best products or services suitable for their taste and needs. A computerized tool called the recommender system (RS) can recommend a variety of items to users according to their preferences by filtering large amounts of data (Bokadia & Jain, 2024).

Recommender systems (RSs) represent a technology designed to continuously advocate items that align with consumers’ preferences and behaviors. They have become ubiquitous on e-commerce platforms, strategically employing messages such as “People who purchased this item also bought...” to enhance opportunities for upselling and cross-selling (Lee & Hosanagar, 2021). By leveraging customers’ purchase histories, an RS generates tailored recommendations and suggestions. By combining artificial intelligence, algorithms, and data structures, RSs aim to streamline users’ search processes and reduce their search costs (Nguyen, 2021; Roy & Dutta, 2022). Currently, recommender systems are being increasingly used for a myriad of applications, such as web (Castellano et al., 2011; Göksefede & Gündüz-Öğüdükü, 2010; Ochi et al., 2010), books (Crespo et al., 2011), movies (Bobadilla et al., 2010), music (Yoshii et al., 2008), tourism (García-Crespo et al., 2011; Lorenzi et al., 2011), e-learning (Bobadilla et al., 2009; Salehi & Kmalabadi, 2012; Wang & Wu, 2011), television (Bjelica, 2010; Shin & Woo, 2009), e-commerce, and news (Roy & Dutta, 2022). Consequently, the development of comprehensive RSs is paramount for delivering personalized recommendations across diverse applications.

Recommender systems (RS) operate within a framework consisting of two key entities: users and items. Users represent individuals who either finalize a purchase or utilize the product. The items encompass the range of products and their variations available for purchase. Typically, RSs furnish users with a list of item preferences expressed through numerical ratings. Subsequently, by leveraging these quantified ratings or feedback, RSs endeavor to recommend unknown items to users (Adomavicius & Tuzhlin, 2005). This process entails making predictions to suggest suitable items to specific user segments. However, this conventional approach to recommendation has limitations. It often relies on a single criterion for evaluating items (Monti et al., 2021). Given that items can be assessed based on multiple criteria, this simplistic approach may prove inadequate. Users frequently assign multiple ratings to each item, which the recommender system can...
manipulate to suggest appropriate items by employing traditional recommendation criteria. Following an exhaustive review of the literature on RSs, the research objectives for this study are delineated as follows:

a) To scrutinize the extant literature to explore the concept of recommender systems in e-commerce.

b) To enlist various types of recommender systems and different constructs studied in the reviewed research.

c) To develop a consequential conceptual research framework to guide future studies on RS.

Given the significance of online shopping and digital marketing in e-commerce, understanding RS dynamics is paramount. It aids the seller in providing direct and comprehensible categorization of pertinent product information to target customers to enhance the purchase experience (Pu et al., 2011). The study empowers marketers to craft targeted strategies, leveraging technological advancements to enhance consumer experiences.

2. Theoretical Background

2.1. Recommender systems and their typology

With the rapid expansion of the internet, e-commerce systems have become increasingly prevalent, becoming an indispensable facet of our daily routines. Platforms such as Amazon.com, Myntra, Flipkart, etc., offer an extensive array of product categories, thereby presenting users and consumers with the formidable challenges of navigating through abundant choices. This dilemma directly impacts consumer purchasing behavior, thus exerting a direct influence on sales metrics (Abdul Hussien et al., 2021). In this context, recommender systems play a pivotal role in optimizing the performance of e-commerce platforms. Therefore, the careful selection and implementation of appropriate RS is vital for any e-commerce website.

The concept of ‘recommender systems’ was originally conceptualized by Elaine Rich in 1979 during her exploration of various methodologies for recommending books tailored to individual user preferences. Her pioneering idea was centered around developing a system capable of analyzing user-specific information to assign corresponding stereotypes, facilitating personalized book recommendations (Beel et al., 2016; Bokadia & Jain, 2024; Rich, 1979). Notably, the term “recommender systems” was first used in a report titled ‘Digital Bookshelf’ by Jussi Karlgren in 1990 (Karlgren, 1990). Using artificial intelligence, RS is a tool that suggests products to customers according to their tastes and preferences (Nguyen, 2021). It is performed by retrieving insights from customers based on their buying behavior or purchase history. Operationally, recommender systems rely on diverse algorithms, with content-based RS, collaborative filtering and hybrid RS emerging as predominant methodologies. (Li et al., 2013; Yan et al., 2016). Moreover, notable advancements have been observed in RS. These include knowledge-based (KB), utility-based (UB), demographic-based (DB), and various other categories. The overarching objective of RS is to recommend important and relevant items only to consumers, hence alleviating the drawback of information overload (Bokadia & Jain, 2024). Among all the existing types of RSs, collaborative filtering (CF) stands out as a widely adopted and effective technique in e-commerce and business (Hwangbo et al., 2018). Furthermore, RSs are embedded in several areas, such as information retrieval (IR), machine learning (ML), decision support systems (DSSs), and knowledge recovery (KR) (Abdul Hussien et al., 2021; Nilashi et al., 2013). Within the e-commerce sector, six primary types of RSs are commonly deployed:

2.1.1. Collaborative Filtering Recommender System (CF-RS)

The CF algorithm is founded on the concept that recommending items to the target customer relies on the preferences of similar customers from the past. The similarity in the previous scores of customers is used to gauge the similarity in the perception of two or more customers (Abdul Hussien et al., 2021; Alhijawi & Kilani, 2020; Nilashi et al., 2013). Widely recognized and extensively applied, CF stands as one of the most favored methods within the RS, notably employed by the Amazon (Alamdari et al., 2020). CF is typically implemented in two principal modes: a) a model-based approach and b) a memory-based approach (Sarwar et al., 2022). Memory-based CF algorithms predominantly fall into two categories – user-based CF and item-based CF algorithms (Iwanaga et al., 2019). Item-based CF establishes the relationships among dissimilar items by analyzing the user-item matrix (Deng et al., 2019). Conversely, user-based CF generates recommendations on the similarity among users by evaluating the likeness between target users and other users (Yi et al., 2016).

2.1.2. Content-based recommender system (CB-RS)

The CB recommendation proposes items that are akin to those previously enjoyed by the customer. The basis for assessing the similarity among the items is the characteristics of the relative products (Abdul Hussien et al., 2021). The system leverages data on consumer preferences and item descriptions to filter and recommend apt items to the user (Alamdari et al., 2020).

2.1.3. Hybrid Recommender System (H-RS)

https://www.malque.pub/ojs/index.php/mr
Hybrid RS is employed to augment RS efficacy by amalgamating various algorithms and techniques, aiming to address the shortcomings of individual RS (Park, 2019). Typically, the amalgamation of CF and CB approaches is integrated to mitigate the limitations of both (Can & Morisio, 2017). This integration leads to more efficient and accurate suggestions for novel items (Aprilanti et al., 2017; Dong et al., 2013).

2.1.4. Knowledge-based recommender system (KB-RS)

KB-RS recommends products conditional on domain knowledge encompassing information about product features and users’ requirements and preferences. It relies on explicit knowledge regarding item recommendation criteria, product categorization and user tastes, effectively addressing the cold-start problem (Alamdari et al., 2020; Brusilovsky & Kobsa, 2007; Monti et al., 2021). The similarity function of KB-RS takes into account both problem information (needs) and issue solutions (matching the recommendation), as well as the number of recommendations a user requires (Fesenmaier et al., 2021). Notably, Google utilizes customer queries for recommendations, serving as a prominent example of KB-RS implementation.

2.1.5. Demographic-based recommender system (DB-RS)

A DB-RS leverages users’ demographic profiles to generate recommendations. These profiles typically include information such as location, language, age, religion and other relevant parameters aiding in the personalized recommendations of the items to users. It is highly valuable and relevant, particularly in e-commerce settings, where it serves as a fruitful solution for discerning users’ interests. (Yuan & Yang, 2017). Consumer demographics play a vital role in RSs, which holds true for e-commerce platforms as well (Cazella et al., 2006; Schafer et al., 1999).

2.1.6. Utility-based recommender system (UB-RS)

UB-RS generates recommendations by assessing the usefulness of a particular product based on user-expressed preferences. These systems employ information with the help of a multiattribute utility function (MAUT) to gather information from item ratings provided by the user, thereby capturing their preferences. The utility calculation is conducted based on the correlation of the search query, product availability, comparison with similar products, seller ranking and other factors. (Burke, 2002; Deng, 2015). This system is utilized to suggest niche products on e-commerce platforms such as Amazon.com. (Five Types of Recommender Systems and Their Benefits, n.d.) UB-RS effectively overcomes several issues encountered in CF-RS, such as cold-start, sparsity and high dimensions (Burke, 2002; Huang, 2011).

2.1.7. Recommender Systems and Consumer Purchase Intention

The intent to purchase is a pivotal decision-making process that delves into the reasons behind a customer’s selection of a particular brand (Akkucuk & Esmaeili, 2016). RSs are designed to enhance consumer purchasing intentions and enrich their experience by offering personalized service. Research findings by (Ku & Tai, 2013) underscore a critical association between recommendation information and consumer attitudes and purchasing intentions (Bokadia & Jain, 2024). Studies such as (Lepkowska-White, 2013) have investigated the impact of online recommender systems on e-commerce websites, aiding marketers in refining their strategies and enhancing consumers’ buying experiences. These investigations also shed light on how recommendations facilitate purchasing decisions. Additionally, (X. Yang, 2020) scrutinized the influence of informative elements on purchase intent in social recommender systems. It also examined the correlation between trust in recommendations and the perceived value of informational components and customer purchase intention.

3. Methodology

In general, researchers undertake systematic literature reviews (SLRs) following the preferred reporting items for systematic review and meta-analysis (PRISMA) protocols (PRISMA-P) coined by (Moher et al., 2009) and (Moher et al., 2015), respectively. While both PRISMA and PRISMA-P facilitate SLR in a well-ordered, clear and diligent manner, they were primarily designed for general SLRs and offered limited criteria for research to elucidate and justify their review decisions. (Paul et al., 2021). In response to these constraints, a newly developed alternate review protocol called the SPAR-4-SLR protocol has been used; this protocol addresses these limitations by providing a framework for justifying review decisions while ensuring efficiency and efficacy (Paul et al., 2021).

The SPAR-4-SLR protocol comprises three stages and six sub stages presented sequentially, as depicted in Figure 1, to facilitate synthesis in the literature.

3.1. Assembling

Assembling encompasses two sub stages, i.e., identification and acquisition.

In the identification stage, the study emphasizes locating the documents in the realm of the recommender system and the pertinent information to address the research questions (RQ1-RQ3) outlined in Figure 1. The source type is restricted to
journal articles and conference papers because they are fundamental sources for scholarly contributions to the literature. Conversely, other sources, such as books, etc., are deemed more explanatory than contributory.

In the acquisition stage, Emerald Insight, IEEE Xplorer, Science Direct, Scopus, Springer and Taylor and Francis were utilized due to their provision of high-quality and reliable documents. The screening of online research articles employed 5 descriptors: “Recommender systems”, “Recommendation systems”, “Recommend* System*”, “E-commerce”, and “Consumer Purchase Intention*”. A total of 908 journal articles and conference proceedings were screened, as illustrated in Figure 2.

**Figure 1** Review procedure using the SPAR-4-SLR protocol. (*Scientific Procedures and Rationales for Systematic Literature Reviews*) protocol.

### 3.2. Arranging

The arrangement consists of two sub stages—organization and purification.

In the organization stage, filters, referred to as codes, including language, document type, source type and subject area, were applied, resulting in 908 search results.

In the purification stage, documents published as journal articles and conference proceedings were specifically selected in the English language. Given the interdisciplinary nature of research in the field of RSs, the subject area was
confined to business, management and accounting, economics and finance due to its relevance across various domains. The following categories were excluded from the research:

- Books and news articles.
- Master’s dissertations.
- Papers in any language other than English.
- Unpublished papers.
- Journal and conference papers published before 2010.

Of the 358 documents screened based on the above parameters, 60 were ultimately chosen for further review. Initially, a total of 908 journal articles and conference proceedings were obtained from the search results, from which 358 documents were screened. Finally, 60 articles were selected based on titles, keywords and abstracts that specifically addressed the integration of consumers with recommender systems.

3.3. Assessing

This assessment encompasses two sub stages, namely, evaluation and reporting.

In the evaluation stage, various analysis methods were incorporated. Papers were initially selected based on keywords and titles. Notable authors contributing to this field include (Adomavicius et al., 2013; Lee & Hosanagar, 2021; Martinez-López et al., 2010). Content analysis was conducted to identify theories, trends and constructs. Software tools such as MS Excel and MS Word were used for descriptive and content analysis. Variable clustering was performed to establish a relationship between similar variables. Furthermore, a gap analysis was conducted to identify and report gaps in the literature. The managerial implications and future research directions are delineated in the subsequent section.

The reporting stage presents the findings of the review in the subsequent section.

3.4. Sources and Paper Selection

<table>
<thead>
<tr>
<th>SOURCE</th>
<th>TOTAL SEARCH RESULTS IN STAGE 1</th>
<th>SHORT-LISTED PAPERS IN STAGE 2</th>
<th>SELECTED PAPERS IN STAGE 3</th>
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<td>Emerald Insight</td>
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Figure 2 The inclusion and exclusion process for arranging the records for the final study.
4. Results

Recommender systems have the potential to significantly benefit users when sufficient information about their tastes and preferences is available (Yeung, 2015).

RSs offer numerous advantages for consumers:

- **Personalization:** The RS supplies tailored product or content recommendations based on individual tastes and preferences, amplifying user satisfaction (Adomavicius et al., 2008; Häubl & Murray, 2003).

- **Serendipity:** An RS can introduce users to unexpected, enjoyable items or experiences, fostering serendipitous moments (Zhang et al., 2012; Ziarani & Ravanmehr, 2021).

- **Reduced information overload:** The RS assists in filtering the most suitable options, averting the users from feeling overwhelmed by too many choices (Monti et al., 2021; Roy & Dutta, 2022).

- **Time-saving:** RSs reduce the time spent searching for suitable items, simplifying the process for users.

- **Enhanced user experience:** When consumers receive recommendations aligned with their preferences, overall satisfaction increases. (Häubl & Murray, 2003)

- **Potential cost savings:** RS can help users find deals, discounts and cheaper alternatives.

- **Improved decision-making:** Users can make informed choices because the recommendations are dependent on the purchase history, reviews and ratings of the other customers (Adomavicius & Tuzhilin, 2005).

- **Discovery:** They help users become aware of new products and services in the market they did not know about, thus providing them with more variety and satisfaction.

- **Increased engagement:** Personalized recommendations can keep users engaged with a platform or services for longer periods (Choi et al., 2017; Wang & Wu, 2011).

4.1. Factors impacting the efficacy of the recommender system

Among the 60 papers reviewed, key factors impacting the recommender system and their efficacy were shortlisted and mapped with synonyms used by different researchers. Ten critical variables pertinent to recommender systems and websites were selected for further investigation to establish a model.

These variables include –

- Attitude toward RS
- Awareness of RS
- Trust in the RS
- Social presence
- Product (Product Price; Product Preference; Product Profile)
- Customer (user profile; consumer review and ratings; willingness to buy)
4.1. Attitude toward RS

Attitude refers to a feeling or opinion regarding something, particularly consumers’ attitude toward RS, which was originally adapted from the Technology Acceptance Model (TAM) introduced by (Davis, 1989). Within marketing psychology, there is a widely accepted framework that seeks to delineate attitude dimensions: cognitive, affective and behavioral (Hubert & Kenning, 2008).

The following are the various factors that have been clustered together under the head of attitude toward RS: attitude toward recommendations (Lepkowska-White, 2013; Martínez-López et al., 2010; Zhang & Bockstedt, 2020), attitude toward websites (Jeong & Lee, 2013), attitudes (Yunhui et al., 2022), and attitude toward vendors’ recommendations (Martínez-López et al., 2015; Martínez-López et al., 2015)

4.1.2. Awareness

Awareness in the context of RS pertains to knowledge, perception or familiarity regarding RS as well as the products and brands suggested by it.

The following are the various factors that have been clustered together under the head of awareness: awareness (L. Li et al., 2018), awareness (He et al., 2014), average awareness (Wu et al., 2013), product awareness (Wu et al., 2013), attention to recommendation (Martínez-López et al., 2010), knowledge of product class (Baum & Spann, 2014), knowledge (Alyari & Jafari Navimipour, 2018), semantic knowledge (Huang et al., 2020), and familiarity with RS (Martínez-López et al., 2015; Roudposhti et al., 2018; Zhang & Bockstedt, 2020)

4.1.3. Trust in Recommendations
Trust refers to a firm belief in reliability or truth and has often been conceptualized as a multidimensional concept (McKnight et al., 1998, 2002). Information on trust was acquired from the trust-TAM model coined by (Gefen et al., 2003). In the context of this study, trust represents overall trust in products, recommendations and websites.

The following are the various factors that have been clustered together under the head of Trust in Recommendations: Trust (Choi et al., 2011; Panniello et al., 2016; Roudposhti et al., 2018); General Trust (Martínez-López et al., 2010); Trust in Vendor’s RS (Martínez-López et al., 2015); Trust in Recommendations (Yang, 2020)

4.1.4. Social presence

Social presence refers to the degree to which a medium allows the user to create a personal connection with others, influencing the attitude of users toward a website (Choi et al., 2017).

The following are the various factors that have been clustered together under the head of Social Presence: Social Presence (Choi et al., 2011, 2017); Social Influence (Christensen & Schiaffino, 2014); Social Contagion (Virdi et al., 2020); Social Proof (Lina et al., 2022)

4.1.5. Product Price

Product price plays a significant role in influencing user decisions. Pricing strategies play an essential role in modern electronic business (Hamian et al., 2018). It also influences the behavior of the target market to fulfill marketing objectives, increasing revenue and margins.

The following are the various factors that have been clustered together under the head of product price: product price (Beladev et al., 2016; Köhler, 2016; Li et al., 2018); price/pricing (Lee & Hosanagar, 2021; Wakil et al., 2020; Zhang & Bockstedt, 2020; Zhou et al., 2022); price level (Kim et al., 2022); price promotion (Zhao et al., 2018); price bundling (Beladev et al., 2016); and product list price (Lin, 2014)

4.1.6. Preference

Preference refers to the user’s inclination toward a product over other available options. It varies from user to user. It is a subjective concept that depends on past experiences, psychological desires and physiological status (Li & Wong, 2006).

The following are the various factors that have been clustered together under the head of preference: preference (Adomavicius et al., 2013; Christensen & Schiaffino, 2014; Congying et al., 2016; Li et al., 2017; Ma et al., 2017; Zhang & Bockstedt, 2020); customer/user preference (Cha et al., 2019; Chinchanchokchhai et al., 2021; Jiao et al., 2016; Ma et al., 2017); brand preference (Zhou et al., 2022); most preferred product (Köhler, 2016); interest and needs (Khodabandehlou et al., 2021); and relevance to personal interest (Ku & Tai, 2013).

4.1.7. Product Profile

A product profile is a set of product-related information consisting of product specifications, technical details, design elements, etc., providing an understanding of the product. Recommendations are formulated based on the rating history of past users and similarities between product profiles and user profiles.

The following are the various factors that have been clustered together under the head of a product profile: product profile (Abdullah et al., 2010; Badriyah et al., 2017; Beladev et al., 2016; Congying et al., 2016; Ma et al., 2017; Yadav et al., 2018; Yunhui et al., 2022); product type (Choi et al., 2011; Deng, 2020; Lee & Hosanagar, 2021; Lina et al., 2022; Virdi et al., 2020); product attribute (Cha et al., 2019; Cheng et al., 2018; Jiao et al., 2016); product properties (Cha et al., 2019); product features (Yin et al., 2018; Zhu et al., 2010); product class/classification (Baum & Spann, 2014; Wakil et al., 2020); product bundling (Beladev et al., 2016); product database (Alyari & Jafari Navimipour, 2018); item features (Christensen & Schiaffino, 2014); and item description (Adomavicius et al., 2013; Christidis & Mentzas, 2013; Gao et al., 2017).

4.1.8. User profile

In an RS, user profiles are associated with the users’ information requirements (Quiroga & Mostafa, 2002). Each user possesses a personal user profile containing historical ratings of items purchased, serving as the foundation for making recommendations.

The following are the various factors that have been clustered together under the head of the user profile: user profile (Abdullah et al., 2010; Badriyah et al., 2017; Chadha & Kaur, 2015; Congying et al., 2016; Deng, 2020; Wakil et al., 2020; Yadav et al., 2018; Yin et al., 2018; Zhang & Bockstedt, 2020); customer profile (Khodabandehlou et al., 2021); user demographics (Heimbach et al., 2015; Khodabandehlou et al., 2021; Zhu et al., 2010); demographic profile (Alyari & Jafari Navimipour, 2018); user description (Adomavicius et al., 2013; Gao et al., 2017); and user database (Priya et al., 2015).
Users provide ratings by employing rating scales, which are graphical widgets characterized by features such as numbering and granularity (Gena et al., 2011). They are a vital piece of information for RSs (Adomavicius & Tuzhilin, 2005). Consumer review consists of feedback provided on a product or service by a user who has purchased, used or experienced it.

The following are the various factors that have been clustered together under the head of consumer reviews and ratings: user ratings (Alyari & Jafari Navimipour, 2018); ratings (Badriyah et al., 2017; Cena et al., 2017; Gao et al., 2017; Lee & Hosanagar, 2021; Ma et al., 2017; Wakil et al., 2020; Yadav et al., 2018); ratings of consumers (Köhler, 2016); rating data (Li et al., 2017); average ratings (Panniello et al., 2016); likes (Heimbach et al., 2015); structured reviews (Abdullah et al., 2010); online reviews (Huang et al., 2020; Ku & Tai, 2013); and consumer reviews (Baum & Spann, 2014; Panniello et al., 2016).

4.1.10. Willingness to Purchase

The behavioral intention of a consumer to purchase a particular product is termed willingness to buy, while willingness to pay refers to the maximum price at or below which a consumer will buy a product.

The following are the various factors that have been clustered together under the head of willingness to purchase: willingness to pay/purchase (Beladev et al., 2016; Köhler, 2016; Scholz et al., 2015; Wu et al., 2013; Zhang & Bockstedt, 2020; Zhao et al., 2018), purchase intention (Choi et al., 2017; Ku & Tai, 2013; Lina et al., 2022; Roudposhti et al., 2018; Yang, 2020; Yunhui et al., 2022), willingness to buy (Beladev et al., 2016; Martínez-López et al., 2010; Martínez-López et al., 2015), purchase (Deng, 2020; He et al., 2014), and purchasing behavior (Khodabandehlou et al., 2021).

4.2. Research Synthesis: Proposed Conceptual Framework

A content analysis was conducted for the articles included in this study to develop a conceptual framework illustrating the antecedents, mediators, moderators, enables and consequences of recommender systems and their impact on consumers. Figure 4 represents this conceptual model, which serves as a foundation for future research and extension. Due to the developmental stage of some constructs and their unclear relationships with other constructs, not all studied constructs were included and mapped into this model.
5. Discussion

The present review offers both theoretical and managerial implications for the field of recommender systems. The theoretical contributions are threefold:

First, this study contributes to the macro-level literature by synthesizing and analyzing the fragmented knowledge surrounding RSs empirically scrutinized in prior research.

Second, it contributes at the micro-level by presenting a conceptual framework that describes the mechanism (antecedents, enablers), modifiers (mediators, moderators) and implications (consequences) of recommender systems and their influence on consumers. This framework not only provides a foundation for advancing knowledge in this field but also offers avenues for future research. It also presents the theories that have been used in this field. While many constructs in the conceptual model have been studied independently in the past, prospective authors interested in carrying out future research may consider (1) adding new constructs; (2) extending the list of constructs in underexplored class (hedonic attributes, situational moderators); (3) examining a broader collection of constructs from the same class; and (4) studying the influence of different categories on RSs.

Third, by elucidating the extant literature, this review identifies several variables and sub-variables that require further scholarly attention. Future researchers can use these constructs to validate more advanced frameworks and comprehensively examine the impact of RSs.

The main managerial contributions of the present study lie in its applicability to managers, e-vendors and e-sellers, online business owners and other individuals involved in online selling and digital marketing.

First, the findings offer insights that can aid in the implementation of updated technology.

Second, they can be used to raise awareness about developments in the domain of RS and assist managers in making informed decisions.

Finally, managers and affiliated groups can gain a holistic understanding and consequently can educate other stakeholders by shedding light on the mechanism (antecedents, enablers), modifiers (moderators and mediators) and implications (consequences) associated with RSs, guiding the design and implementation of RSs in online marketplaces.

5.1. Research Limitations

This research provides guidelines for future research in the domain of RSs. However, this study has certain limitations. While reviewing and documenting the significant literature, technical reports, editorial notes, web pages, and books were excluded, resulting in the review potentially missing some important contributions. Additionally, the selection criteria focused on keywords such as “Recommender systems/Recommender systems”, “consumer” and “e-commerce” in titles to select the relevant papers. However, there may be papers that, although relevant, do not include the specific combination of keywords used in this study. Such items were not considered under the prerogative of this study. These limitations should be recognized in future research endeavors in the domain of RSs.

6. Final Considerations

Recommender systems have garnered considerable interest among researchers and academicians. This systematic literature review analyzed a total of 60 studies published between 2010 and 2022. Recurring constructs were identified, segregated and used to develop a conceptual framework outlining the mechanism (antecedents, enablers), modifiers (moderators and mediators) and implications (consequences).

The analysis revealed that CF-RSs are the most commonly and extensively utilized technique in e-commerce and businesses, followed by H-RSs. Emerging techniques such as UB-RS, KB-RS, and DB-RS presented opportunities for more intensive research. These RS techniques aim to enhance the accuracy of suggested items. Moreover, further research could explore the various domains and applications of RSs.

Among the identified constructs, the product profile emerged as the most discussed. Constructs such as attitudes toward RS, trust in RS and social presence are considered to be emerging and significant, warranting more attention and scholarly research in the future. Furthermore, consumer reviews and ratings were found to exert a significant influence on consumer willingness to purchase. Further research could delve into examining the challenges associated with these constructs in RS implementation.

Ethical considerations

Not applicable.

Conflict of interest

The authors declare that there are no conflicts of interest.

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