Risks of e-commerce Recommender Systems: A Scoping Review

Eranjana Kathriarachchi
School of Management, Massey University
Auckland, New Zealand
Email: e.kathriarachchi@massey.ac.nz

Shafiq Alam
School of Management, Massey University
Auckland, New Zealand

Kasuni Weerasinghe
Management Technology Organisation Department, Auckland University of Technology
Auckland, New Zealand

David Pauleen
Graduate Institute and Department of Business Administration, National Chung Cheng University,
Chia-Yi, Taiwan

Abstract

While recommender systems (RS) used in e-commerce have improved significantly providing customers with a personalised shopping experience, scholars have constantly raised concerns over the risks associated with e-commerce RS. However, a lack of methodological synthesis of risk-generating events associated with e-commerce recommender systems has curtailed systematic investigation of the risks of e-commerce RS. This paper presents a scoping review aimed at addressing this gap by synthesising different risk-generating events involved with the use of e-commerce RS as reported in the literature that could affect the welfare of customers who use those systems. Accordingly, peer-reviewed research studies published from 2003-2023 were extracted from the SCOPUS database and EBSCOhost platform for review. Sixty-two publications with evidence on risk-generating events of e-commerce RS were considered for the review. Twenty risk-generating events were identified through the review. These events were mapped with the corresponding risks based on existing frameworks on risks of e-commerce. We were able to identify several risk-generating events that had not previously been considered in conceptualising the risks of e-commerce RS. Further, we identified the plurality of the outcomes of risk-generating events which could provide guidance for the evaluation of e-commerce recommender systems from a multistakeholder perspective.

Keywords: Risk-generating events, e-commerce, Recommender systems, Scoping review.

1 Introduction

Recommender Systems (RS) predict user preferences using statistical, machine learning, and artificial intelligence (AI) techniques (Jannach et al., 2022; Necula & Păvăloaia, 2023). RS are now being used in many areas such as e-commerce, entertainment, health, education, human resource

Received 30 Oct 2023, accepted 4 July 2024 after 2 rounds of review with Karlheinz Kautz as accepting Editor.

management, online dating, and mobile apps (Mallik & Sahoo, 2020; Pizzato et al., 2013) helping users to steer through complex and large volumes of information. Among these various areas of application, the e-commerce sector has significantly benefited from personalised product recommendations provided by e-commerce recommender systems (hereinafter referred to as e-commerce RS). The global e-commerce sector is expanding rapidly with its revenue expected to grow up to US$ 8.1 trillion by the end of year 2027 from the 2022 level of US$ 5.8 trillion (Chevalier, 2024). E-commerce RS deployed in e-commerce websites play an essential role in assisting customers to navigate through complex product-related information to identify the most suitable products for them (Fabbri, 2022; Murphy, 2011; Vučetić & Hudec, 2018; Xiao & Tan, 2012). The world's leading e-commerce platforms such as Amazon, eBay, Alibaba, and Flipkart are examples that show the significance of RS in the commercial sphere (Jannach et al., 2022; Kiswanto et al., 2018; Kong et al., 2017; Lee et al., 2012; Ram Mohan Rao et al., 2018; Smith & Linden, 2017; Yang et al., 2018).

Despite their contribution towards the success of the e-commerce sector, RS suffer from various issues that affect the welfare of the customers who rely on them. Some scholars have looked at these issues from an ethical perspective (Chen, 2022; Milano et al., 2020; Wang et al., 2023), while others have looked at those from a risk perspective (Glover & Benbasat, 2010; Jannach & Bauer, 2020). Researchers who have taken the risk perspective have proposed several risk classifications based on different ways in which e-commerce RS negatively affect users. These classifications consist of risks such as inferior product decisions, negative user experiences and privacy issues (these will be discussed in detailed in the next section). Although these risk classifications have guided researchers to examine the risks associated with e-commerce RS, we encountered two limitations with these classifications. The first limitation is that the risk classification (e.g., Glover & Benbasat, 2010) is not up-to date with the most recent risk-generating events (i.e. events that could cause harm to users) discussed in the academic literature. The second limitation is that the risk classification (Jannach & Bauer, 2020) was not developed based on a systematic study of different risk-generating events, related to the risks proposed.

This lack of a comprehensive understanding of risk-generating events preempts a comprehensive understanding of risks associated with e-commerce RS. This was particularly relevant to our research team as the first author is engaged in a doctoral research project investigating stakeholder perceptions of risk in e-commerce RS. Against this backdrop, we decided to conduct a study to synthesise risk-generating events associated with e-commerce RS as reported in the literature. Grant and Booth (2009) have identified 14 different types of literature reviews according to differences in intended objective and methodology followed in each type. For example, a critical review is aimed at critically evaluating the quality of literature whereas a meta-analysis is expected to statistically combine the results of quantitative studies to provide more precise effects of the results. According to them, a scoping review enables researchers to identify the size and scope of available research literature. Further, scoping reviews are useful in examining emerging evidence that addresses and informs practice (Munn et al., 2018; Peters et al., 2015). Due to these reasons, a scoping review was deemed suitable for our synthesis of literature. Our scoping review addresses the following research questions:

RQ 1: What risk-generating events do customers encounter when they use e-commerce RS?

RQ 2: How are these risk-generating events potentially linked to the risks of e-commerce RS?

These research questions are addressed by reviewing the literature published during 2003-2023. Risk-generating events and their negative outcomes as reported in the literature were recorded, analysed, and presented to answer the first research question. In addressing the second research question, the risk classification proposed by Jannach and Bauer (2020) was utilized due to its specific focus on e-commerce RS. The process followed is further explained below in the methods section.

The main contribution of this study is a review of evidence on risk-generating events with its potential links to risks of e-commerce RS. Hence, this study is important for a diverse range of stakeholders who rely on e-commerce RS. For customers, knowledge about the events exposing them to potential harm will be important to either avoid or manage such situations for their well-being. E-commerce managers will be able to identify different occurrences which could negatively affect customers and the business and take required action to mitigate their impact. In addition, policy makers and governments can also gain a deeper understanding of different ways in which recommendation technology used in product recommendations could harm the welfare of customers and society in general.

The next section of the paper presents a background to the study, followed by sections on RS in the Information Systems (IS) context, the theoretical underpinning of the study, a summary of existing reviews on e-commerce RS, methods, results, and a discussion.

2 Background

E-commerce RS are defined as "a web-based technology that explicitly or implicitly collects a customer's preferences and recommends tailored e-vendors' products or services accordingly" (Li & Karahanna, 2015, p. 74). Implicit preferences (e.g., customers' online behaviour) and explicit preferences (e.g., customer reviews and ratings) function as the knowledge base to build user profiles (Eryarsoy & Piramuthu, 2014). These user profiles form the basis for providing personalised product recommendations to customers.

Advancements in RS technology have contributed significantly to the development of the e-commerce sector in the recent past with increased revenue for businesses and satisfying experiences for customers (Chen, 2022; Necula & Păvăloaia, 2023). While some authors have commented on the positive contributions, some others have raised concerns over the harmful impact of e-commerce RS. As mentioned before these harmful effects have been discussed from ethics and risk perspective. For instance, Milano et al. (2020) have presented a taxonomy of the ethical challenges of RS such as inappropriate content, privacy, autonomy and personal identity, opacity, fairness, and social effects. This taxonomy is based on whether an ethical issue negatively affects the utility or rights of stakeholders and whether it will constitute immediate harm or a future risk of harm or rights violation. They have further concluded that any aspect of a RS that could negatively affect any of its stakeholders, or risk imposing such negative impacts, constitutes a feature that is ethically relevant.

A risk is defined as "the possibility a negative outcome will occur as a result of exposure to a hazard" (Wilson et al., 2019, p. 780). Similarly, researchers who have taken the risk perspective have looked at different risk-generating events (i.e. hazards) associated with the use of e-commerce RS which cause harm to their users. Glover and Benbasat (2010) have pioneered the use of events which cause harm to customers (which they have referred to as 'unwanted events') to conceptualise risks of e-commerce transactions. They have examined a total of 104 unwanted events ('risk-generating events' in this study) to study customers' risk perceptions towards e-commerce transactions. Among these 104 unwanted events are those associated with the RS deployed in e-commerce platforms. These events have been used to identify the cause of harm (formative measure), which have then been used to conceptualise the risk dimensions. An illustration of their conceptualisation is provided below.

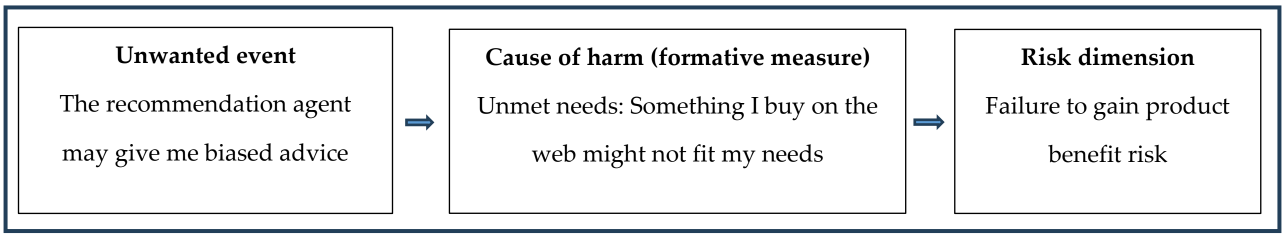

Figure 1 Conceptualisation of risk dimensions based on unwanted events (Glover & Benbasat, 2010)

In this manner based on the unwanted events identified Glover and Benbasat (2010) have conceptualised three types of risks namely, 'information misuse risk', 'failure to gain product benefit risk', and 'functionality inefficiency risk', to construct a model of the perceived risks of e-commerce transactions.

In a more recent study, Jannach and Bauer (2020) have proposed a classification of risks that are specific to RS deployed in e-commerce platforms. According to them, poorly designed e-commerce RS can lead to poor product decisions by customers and negative user experience. Biased information can expand to community-related risks, and misuse of customer information can lead to privacy risks. The classification they have proposed consists of four types of risks namely: poor decision/choice dissatisfaction, bad user experience/decision difficulty, biased information state, and privacy. In essence, except for the risk of 'biased information state' proposed by them, the other three types of risks are similar to the risk classifications proposed by Glover and Benbasat (2010). A comparison of the two classifications is provided in Table 1.

Types of risks (Glover & Benbasat, 2010)	**Types of risks (Jannach & Bauer, 2020)**	**Explanation**
Failure to gain product benefit risk	Poor decision/choice dissatisfaction	Bias introduced by a RS leading to an inferior product purchase decision
Functionality inefficiency risk	Bad user experience/decision difficulty	Poorly designed RS and unhelpful recommendations leading to poor user experience
Information misuse risk	Privacy	Unsolicited collection and use of confidential information

Table 1 Comparison between risk classifications

Although these two risk classifications have provided crucial understanding of the risks unique to e-commerce RS, the limitations associated with them have instigated the need to conduct a comprehensive synthesis of evidence related to e-commerce RS. To elaborate, the risk classification proposed by Glover and Benbasat (2010) does not cover certain more recent risk-generating events such as shilling attacks/profile injection attacks (Laskar et al., 2023; Xu et al., 2022), user decision biases (Ahmed et al., 2022; Gu et al., 2020), and algorithmic opacity (Chen, 2022; Eslami et al., 2019) which have received significant scholarly attention. Shilling attacks/profile injection attacks on RS could lead to undesirable items being recommended to customers and in turn their loyalty towards the recommendation systems may decrease significantly (Singh et al., 2022). Researchers (Ahmed et al., 2022; Teppan & Zanker, 2015) are of the opinion that decision biases associated with RS can lead to sub-optimal decision making among users and can be proactively exploited for persuading users. Not only do these inferior decisions of customers pose potential harm to their own wellbeing but such decisions will also lead them to play a role in propagating systemic biases that can influence other customers (Banker & Khetani, 2019). Further, customers' lack of awareness of how algorithms work coupled with their overreliance on recommendation algorithms (Banker & Khetani, 2019) could lead to undesirable outcomes for customers due to biased and deceptive decisions supported by algorithmic opacity (Eslami et al., 2019).

On the other hand, the risk classification proposed by Jannach and Bauer (2020) was not developed based on a systematic study of different risk-generating events related to the risks proposed. This limits our understanding of specific instances that could lead to the types of risks identified in their classification. Hence, we expect that this scoping review will help the academic community as well as the wider stakeholders (customers, managers, and policy makers) to determine the risk potential of current e-commerce RS. The next section of the paper presents an account of e-commerce RS research within the domain of IS research.

2.1 Recommender Systems in the Information Systems context

RS has been extensively studied within the Information Systems (IS) context. This is mainly triggered by IS scholars' focus on user perspectives and the interplay between computerized systems and users (Jannach et al., 2012). These scholars have looked at many topics of interest to both the academic community and practitioners interested in RS (see Table 2 for a summary).

Biases in product recommendations, privacy issues, user engagement and satisfaction are some of the key concerns explored by IS scholars. This scoping review will further assist IS scholars to understand the nature of different events and their potential links with specific risks of e-commerce RS. Further the present study synthesises risk-generating events reported in multiple disciplines such as marketing, computer science and decision support systems. This will be beneficial for IS scholars to understand the inter-disciplinary nature of the research context. The next section of the paper highlights the theoretical underpinning of this study and prior reviews that have been conducted on e-commerce RS.

Studies	Focus/Key findings of the study
Ebrahimi et al. (2022); Hu et al. (2017)	Importance of quality in product recommendations
Ho et al. (2017); Jiawei Chen et al. (2023); Silva et al. (2019)	Biases associated with human decision making in the context of e-commerce RS
Adomavicius et al. (2018)	Role of e-commerce RS in economic decision making. Biases associated with product recommendations leading to customer dissatisfaction which in turn results in reduced willingness to pay
Jannach and Jugovac (2019)	E-commerce RS as a vital tool which fosters revenue/profitability, user engagement, loyalty and customer satisfaction
Lee and Hosanagar (2019)	Collaborative filtering techniques lead to low sales diversity, biased product recommendations will lead to overall decrease in sales diversity
Awad and Krishnan (2006); Xin et al. (2023)	Privacy concerns associated with potential data leakage in e-commerce RS.

Table 2 Summary of the RS research within the IS context.

2.2 Theoretical underpinning and prior reviews

The Model of Perceived Risk of E-commerce Transactions (Glover & Benbasat, 2010) and the psychometric paradigm (Slovic, 1987) provides the theoretical underpinning for this scoping review. These two theoretical frameworks emphasise the significance of examining harmful events in conceptualising risks. For instance, Glover and Benbasat (2010) have opined that identifying the negative outcomes of unwanted/harmful events (similar to risk-generating events in this study) to customers is the best approach to conceptualise the risks associated with IT-based applications rather than looking at the 'source of risk' (the environment, object, or actor) or 'type of harm' (financial loss, time loss, psychological harm). In addition, the psychometric paradigm also prescribes examining harmful events (i.e. hazards) in exploring risk perceptions. The psychometric paradigm has been applied by researchers to elicit judgements on diverse hazard scenarios within a single technological domain where users' risk perceptions estimated based on their evaluations of riskiness in hazards scenarios (Slovic, 1987).

We were able to identify several prior reviews on e-commerce RS which have looked at diverse areas of interest. Recent studies have examined different negative effects of e-commerce RS. For instance, researchers (Alamdari et al., 2020; Nasir & Ezeife, 2023; Stalidis et al., 2023) have consistently shown the negative effect of a lack of diversity in search results and the inability to recognize changing customer preferences on the user experience. Increased privacy concerns among the public due to large volumes of personal information collected by RS to provide better recommendations has also attracted the attention of some scholars (Alamdari et al., 2020). The present study also coincides with these recent reviews which look at the negative effects of RS with a specific focus on e-commerce RS. A summary of the prior reviews on RS is presented in Table 3. The next section of the review details the methods of the present study.

Study	Time period	Sample size	Analysis method	Key focus/findings
Karimov (2016)	2014-2016	60	A literature review of empirical studies	Traditional RS techniques which play a dominant role in e-commerce RS
Wei et al. (2007)	Not mentioned	29	A literature review of empirical studies	There is less research on the application value of RS from other disciplines perspectives (i.e., Management, Marketing, and Psychology) than Computer Science
Li and Karahanna (2015)	1990-2013	41	A literature review of empirical studies	RS literature is fragmented and lacks an overarching framework to guide research and integrate findings. More research is required on interaction between components of RS and the impact
Nasir and Ezeife (2023)	Not mentioned	73	A literature review of empirical studies	A classification and a taxonomy of sequential recommender systems
Stalidis et al. (2023)	2012-2023	296	A literature review of empirical and review studies	Recent trends in RS research namely: balancing accuracy with user expectations, contextual factors, trust, explainability, multiple sources of information available for users, and emergence of neural networks as a technique used in e-commerce RS
Xiao and Benbasat (2007)	1990-2007	47	A literature review of empirical studies	A conceptual model consisting of 28 propositions stemming from five theoretical perspectives
Xiao and Benbasat (2014)	2006-2012	34	A literature review of empirical studies	Studies published between 2007 and 2012 have extended the authors' conceptual model (Xiao & Benbasat, 2007). RS type, preference-elicitation, explanation, and the social impact of RS have been identified as key research areas
Deldjoo et al. (2023)	2014-2023	50 +	A literature review of empirical studies	Critical challenges in fashion RS research and has proposed a taxonomy of objectives that the studies under review have attempted to achieve
Adolphs and Winkelmann (2010)	2000-2008	42	A literature review of empirical studies	A classification of literature on personalisation research in e-commerce under three major categories: implementation, theoretical foundations, and user-centric aspects
Alamdari et al. (2020)	2008-2019	33	A systematic literature review	A comparison and an evaluation of different mechanisms used in e-commerce RS: most of the studies have focused on improving the accuracy of recommendations, and security, response time, and novelty, whereas serendipity has received scant attention

Table 3 Summary of reviews on e-commerce RS

3 Methods

According to Peters et al. (2015), scoping reviews are useful for synthesising existing literature and often are referred to as a 'mapping' exercise. The authors screened scientific literature with the objective of identifying publications that included a discussion on risk-generating events and risks customers face with RS deployed in e-commerce. The concepts were identified to cover this objective and to facilitate developing a comprehensive search query. The identified publications were then reviewed to map existing scholarly evidence of risk-generating events. The search was conducted through the SCOPUS database and EBSCOhost platform. Table 4 outlines the concepts and the respective search terms used.

Concept	**Search terms**
Recommender systems	"recommend* system*" OR "recommend* agent*"
Context	AND e-commerce OR e-business OR "electronic commerce" OR "digital business" OR "online business" OR "online retailing"
Risks	AND risk* OR concerns* OR threats* OR "privacy risk*" OR "bias*" OR "functional risk*" OR "financial risk*" OR "time risk*" OR "psychological risk*" OR "social risk*" OR "product risk"
Users	AND customer* OR user* OR consumer* OR client*

Table 4 Concepts and search terms

Inclusion and exclusion criteria were applied in selecting the publications for this review. In line with the aim of this scoping review, only studies exploring/referring to risk-generating events and their outcomes of using e-commerce RS from customers' perspectives were considered for this review. Only peer-reviewed studies (journal articles, conference papers, and reviews) were included in this review due to their higher validity compared to other types of publications. Studies conducted during 2003-2023 (see Figure 2) were considered because most of the scholarly work in the field of e-commerce RS has been conducted during this time. Only English language publications were considered for this review.

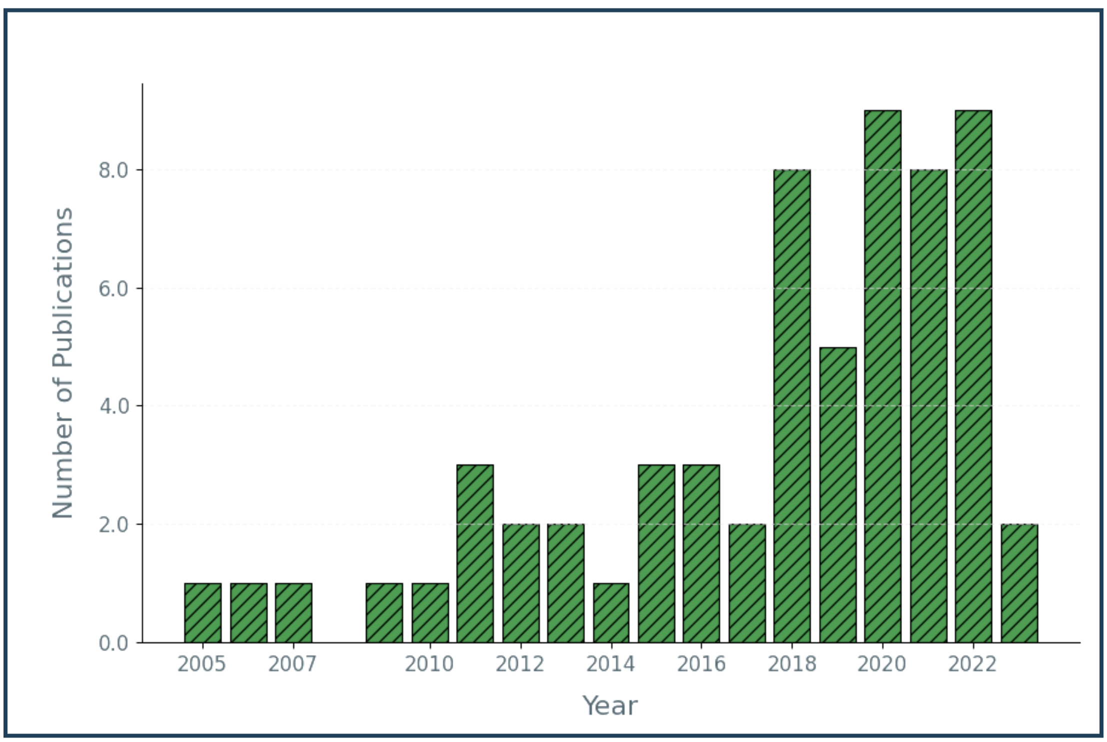

Figure 2: Number of publications per year

Preferred Reporting Items for Systematic Reviews and Meta Analysis (PRISMA) guidelines (Tricco et al., 2018) were followed in selecting publications for the review: the flow chart is shown in Figure 3. The first and second authors were involved in the article screening process independently. The third author was consulted in managing any discrepancies that emerged during the process. Separate search queries were developed independently by the first and second authors and later combined to reduce the biases in executing the search. A total of 417 records were identified in the initial search. Then the search results were compared, and duplicates were

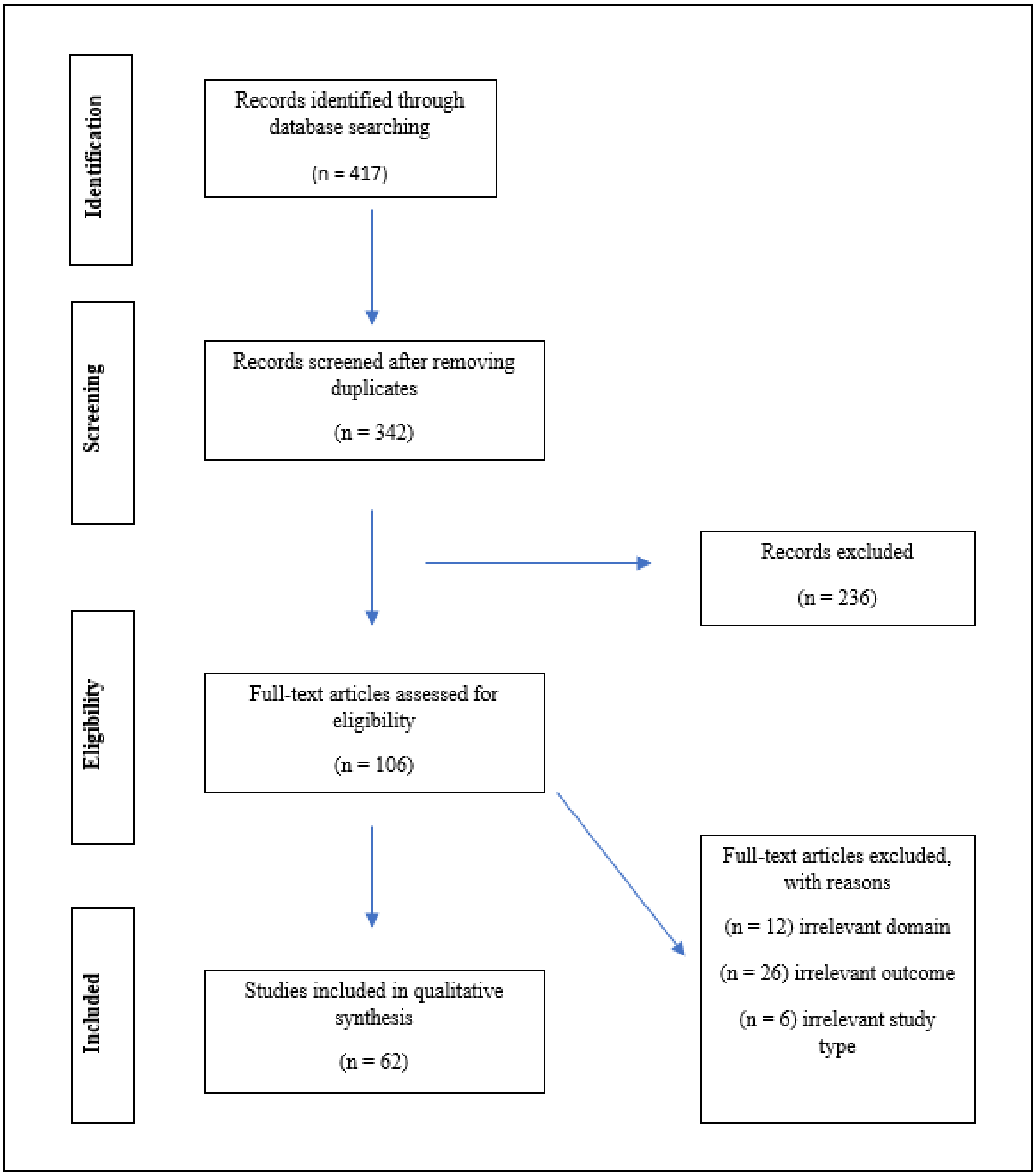

Figure 3: PRISMA Flow Diagram

removed. Next all publications were screened based on the title and the abstract. At this stage of screening, publications that were considered irrelevant based on the inclusion criteria were excluded. The next stage involved reading the selected articles (106 publications). Forty-four articles were excluded after the full-text review for the following reasons: irrelevant domain (not e-commerce sector), irrelevant outcome (absence of risk-generating events or outcomes), or irrelevant study type.

Sixty-two articles were identified as suitable for this review (see Table A1 in Appendix for details on the selected publications). The data extracted comprised author details, the type of risk-generating-event/s reported, and their negative outcomes. The third author reviewed a sub-sample of twenty papers to ensure the validity of the data characterization.

A thematic content analysis was conducted on the data extracted, with the purpose of identifying common themes from each type of risk-generating event reported, resulting in risks of the e-commerce RS from customers' perspectives, according to the inclusion criteria. As suggested by Vailati Riboni et al. (2020), categories were not predefined to avoid the risk of bias, and the classification was entirely conducted retrospectively. The step-by step approach for thematic analysis proposed by Nowell et al. (2017) was used as a guide in deriving the themes. Initially the first and third authors spent time familiarizing themselves with the data. The second step was to generate initial codes based on the risk-generating events and negative outcomes reported. After that, searching and reviewing of themes were conducted with researcher triangulation with the participation of first, second, and third authors. Finally, four themes (hereinafter referred to as categories) were defined and named with the consensus of researchers based on the sources of the events. The next section of the review details the results obtained through the analysis of selected publications.

4 Results

Studies that were considered for the review were labeled according to the risk-generating event/s reported. A total of twenty such events were identified through the review and were classified into four main categories namely,

1. Biased recommendations
2. Malicious activities
3. Customer biases/actions
4. Incompetent systems

See Table 5 for a summary of risk-generating events reported in the studies reviewed (see Table A2 in Appendix for a detailed list of risk-generating events, their negative outcomes, and authors). An analysis of the reviewed studies' most frequent keywords (based on titles, keywords, and abstracts) and the use of keywords over the years is presented in Figure A1 and A2 in Appendix, respectively. In the next section, a detailed analysis of the publications reviewed highlighting the risk-generating events and their links to the risks of e-commerce RS are presented according to the four categories stated above.

Categories	Risk-generating events
Biased recommendations	Recommending popular products (popularity bias), less frequently purchased products, and/or ignoring unpopular/new/obscure products (long tail products)
	Presenting selective/incomplete information or hiding product information
	Promoting profitable products/un-profitable products
	Use of biased/unbalanced user data to provide biased product recommendations to first time/lesser-known customers
	Generating biased system ratings which influence subsequent customer preference ratings (anchoring effect)
	Lacking the surprise element (i.e., serendipity) and/or diversity in recommendations
	Presenting visually biased product recommendations and/or using biased marketing cues to promote products
	Biased policies on exposing search results to customers (exposure bias)
Malicious activities	Shilling/ Profile injection attacks (push and/or nuke attacks) by malicious users
	Dishonest ratings by non-malicious users
	Obtaining, tracking, storing, using, or divulging sensitive customer information in an unauthorized or undesired manner
	Re-using product reviews (review plagiarism) for unwarranted purposes
Customer biases/actions	Customers complying with the choices of other customers (conformity/social influence bias)
	Customers providing biased reviews on products are influenced by the order sequence in which existing online reviews are displayed to a new customer (sequential bias)
	Customers' decision biases (irregularities in human decision making) e.g., the tendency to make decisions under the influence of certain emotional states and/or interests
	Customers contributing to data leakages
	Customers' tendency to favour a product simply because it is ranked high (position bias) or neighbouring/related items influencing click-through rate of a target item (neighbouring bias)
	Customers' lack of awareness of how algorithms make product recommendations
Incompetent systems	Incompetent recommender systems with functional issues (i.e., non-consideration of complex user requirements, information overload, etc.)
	RS not capturing changing user preferences on products over time (user and item bias)

Table 5: Summary of the risk-generating events associated with e-commerce RS

4.1 Biased recommendations

Biases associated with RS have attracted significant scholarly attention from researchers. A summary of the risk-generating activities categorized under biased recommendations is presented in Table 6. According to Wang et al. (2018), biased RS recommend products that do not fit users' indicated preferences. Researchers over the years have explored many ways in which biases occur in RS. One such instance is the presence of popularity bias, where an e-commerce RS recommends popular products (Chen, 2022; Gu et al., 2020; Kiswanto et al., 2018; Lee et al., 2012; Niu et al., 2019; Sreepada & Patra, 2021; Wang et al., 2022, 2022; Zeng et al., 2021). Some authors have referred to this as the 'concentration bias' (Deng et al., 2020; Fleder & Hosanagar, 2009). While popular products are recommended based on the purchase ratings, certain e-commerce sites engage in promoting either profitable products or un-profitable/less popular products (Panniello et al., 2016; Vučetić & Hudec, 2018; Wang et al., 2018; Wang et al., 2018; Xiao & Benbasat, 2015, 2018) with the expectation of achieving high profitability or as an inventory management tactic (Adomavicius et al., 2013; Fabbri, 2022; Xiao & Benbasat, 2015). There have also been situations where companies recommend products that fit customers' preferences, but the product lists are sorted to provide prominence to a product with the highest price or a newly released product. Wang et al. (2018) have referred to this as 'exposure bias', where a pre-determined policy biased towards the interest of the company is used in arranging the order of product recommendations. They have observed that leading e-commerce platforms such as Amazon sometimes provide recommendations that are in favour of their sponsors regardless of their relevance to the customer due to the financial benefits, which results in customer exploitation.

Risk-generating events	Source/s
Recommending popular products (popularity bias), less frequently purchased products, and/or ignoring unpopular/new/obscure products (long tail products)	*Deng et al., 2020; Fleder & Hosanagar, 2009; Gu et al., 2020; Kiswanto et al., 2018; Lee et al., 2012; Niu et al., 2019; Sreepada & Patra, 2021; Vučetić & Hudec, 2018; Wang et al., 2022; Zeng et al., 2021*
Presenting selective/incomplete information or hiding information	*Kim et al., 2017; Xiao et al., 2020*
Promoting profitable products/un-profitable products	*Panniello et al., 2016; Wang et al., 2018; Xiao & Benbasat, 2015, 2018*
Use of biased/unbalanced user data to provide biased product recommendations to firs time/lesser-known customers	*Hu et al., 2017; Silva et al., 2019; Trakulwaranont et al., 2022*
Generating biased system ratings which influence subsequent customer preference ratings (Anchoring effect)	*Adomavicius et al., 2013; Fabbri, 2022; Xiao & Benbasat, 2015*
Lacking the surprise element (i.e., serendipity) and/or diversity in recommendations	*Fabbri, 2022; Ge et al., 2020; Grange et al., 2019*
Presenting visually biased product recommendations and/or using biased marketing cues to promote products	*Qiu et al., 2021; Wan et al., 2020*
Biased policies on exposing search results to customers (exposure bias)	*Wang et al., 2022*

Table 6: Summary of the risk-generating events (biased recommendations)

The problem with continuously promoting popular products might be considered trivial since customers are already aware of popular items and they themselves can make the decision without the support of a recommender system (Hu et al., 2017). However, researchers have pointed out that these biases towards popular/similar products or unpopular products have led to negative customer experiences, distrust (Panniello et al., 2016; Zeng et al., 2021), and standardization and homogenisation of customer choices (Fabbri, 2022), foregoing better customer-product matches, potentially leading to balkanization/herding (Fleder & Hosanagar, 2009). This is because customers are looking for the products they really need rather than the higher-rated items (Niu et al., 2019) or else they seek novelty, diversity, and serendipity (i.e., the ability to surprise and delight customers with relevant and novel recommendations) in lists of product recommendations (Eryarsoy & Piramuthu, 2014; Fleder & Hosanagar, 2009; Ge et al., 2020; Grange et al., 2019; Kiswanto et al., 2018). In addition, some customers who lack awareness might rely on biased product recommendations assuming personalised recommendations have made their decision making easier (Xiao & Benbasat, 2018), but ultimately making poor product decisions.

System-generated ratings are expected to indicate customers' preference for a certain product that was recommended (Adomavicius et al., 2013), and they are becoming indispensable for customers who are seeking product recommendations (Eryarsoy & Piramuthu, 2014). However, Adomavicius et al. (2013) have identified that if the initial output of a recommender system is biased it can have an anchoring effect on the subsequent ratings provided to a product by a customer since customers' preference ratings are malleable and can be significantly influenced by the recommendation they receive (Necula & Păvăloaia, 2023). Further, when providing recommendations for a new customer, the RS faces the problem of a lack of data to provide personalised recommendations, which is referred to as the 'cold-start' problem. Ahmed et al. (2022) and Silva et al. (2019) have advocated that, although when faced with a cold start problem the conventional wisdom is to suggest popular products, that might not be wise as there are instances where unpopular products which are not prioritized by the RS are liked by customers who are new to the system.

Biases associated with the information provided by RS have also received attention from researchers. For example, Kim et al. (2017) and Xiao et al. (2020) have identified that e-commerce companies sometimes intentionally provide selective/incomplete information or hide vital information when providing product recommendations to customers. According to them, biased information influences customers' subjective comprehension of the products available, thereby causing negative user experience (i.e., due to not meeting users' preferences and low-quality results). In addition, the use of visually biased marketing cues is also an instance where intentional manipulations are practiced by e-commerce firms. The literature provides evidence of two kinds of such manipulations. The first is the use of visually biased recommendations which refer to the highlighting of one feature of a product to attract the customer. According to Qiu et al. (2015), sometimes a customer might become dissatisfied when other features that are important for evaluating a product are not highlighted, which could lead to a declined purchase. The second is the use of biased marketing cues which may result in the underrepresentation of niche market segments in the input data for a recommender system (Wan et al., 2020). For example, a gender-neutral product like an armband marketed exclusively via a 'male' image might get less attention from female users. As a result of this, a customer representing a niche market segment might experience difficulties in locating a suitable product within the e-commerce platform. Risk-generating events classified under malicious activities are examined in the review's next section.

4.2 Malicious activities

The literature provides evidence of different malicious activities associated with e-commerce RS. Risk-generating events identified as malicious activities are shilling/profile injection attacks, dishonest ratings by users, unsolicited use of customer data, and review plagiarism (see Table 7 for a summary). Many authors (Chopra & Dixit, 2021, 2023; Moradi & Hamidi, 2023; Xu et al., 2022) in this review identified the shilling or profile injection attacks on e-commerce RS. In shilling or profile injection attacks, malicious users create biased profiles in e-commerce RS with the aim of influencing the system's behaviour and the list of recommendations (Singh et al., 2022; Zhang & Sheng-hua, 2007). Shilling attacks are classified into two areas namely, push and nuke attacks. Push attacks are aimed at manipulating the systems to recommend one or more products to more users whilst nuke attacks are aimed at making a targeted product or products less likely to be recommended (Chopra & Dixit, 2021, 2023; Singh et al., 2022). For example, malicious users intentionally engage in push attacks by injecting higher ratings to increase the recommendations for a product and alter the genuine list of recommendations (Chopra & Dixit, 2021; Huang et al., 2021). Further, malicious users leave negative reviews or low ratings on products that have no resemblance to the quality of the respective product (Chopra & Dixit, 2021; Xu et al., 2022). Sybil attacks are also related to shilling/profile injection attacks where malicious users create multiple fake profiles to inject false recommendations resulting in inappropriate recommendation lists (Chopra & Dixit, 2021). Even popular e-commerce platforms such as Amazon have come under these kinds of attacks and such attacks are aimed at affecting the recommendations provided to genuine customers (Chung et al., 2013; Yang & Cai, 2017).

Risk-generating events	Source/s
Shilling/ Profile injection attacks (Push and/or Nuke attacks) by malicious users	*Aghili et al., 2011; Alamdari et al., 2020; Cai & Zhu, 2019; Chopra & Dixit, 2021, 2023; Chung et al., 2013; He et al., 2010; Hu et al., 2017; Huang et al., 2021; Kumar et al., 2015; Moradi & Hamidi, 2023; Singh et al., 2022; Wei & Shen, 2016; Xu et al., 2022; Yang et al., 2018; Yang & Cai, 2017; Zhang & Sheng-hua, 2007*
Dishonest ratings by non-malicious users	*Cai & Zhu, 2019*
Obtaining, tracking, storing, using, or divulging sensitive customer information in an unauthorized or undesired manner	*Alamdari et al., 2020; Chen, 2022; Erkin et al., 2012; Frey et al., 2016; Hsieh, 2011; Jeyamohan et al., 2019; Kashani & Hamidzadeh, 2020; Li et al., 2021; Lu & Shen, 2015; Mallik & Sahoo, 2020; Mican et al., 2020; Polat & Du, 2005; Ram Mohan Rao et al., 2018; Ran et al., 2022; Rohden & Zeferino, 2022; Vučetić & Hudec, 2018; Yan & Tang, 2011*
Re-using product reviews (Review plagiarism) for unwarranted purposes	*David & Pinch, 2006*

Table 7: Summary of the risk-generating events (malicious activities)

Like shilling/profile injection attacks, there are also instances where malicious users manipulate product reviews, which are supposed to guide genuine customers and are used as input data to make product recommendations to customers (Ahmed et al., 2022). Review plagiarism as identified by David and Pinch (2006) is a similar issue where product reviews are re-used by users for different purposes such as promoting their own products, opinions, or agenda, attacking others, or identity building. There are situations where dishonest ratings/reviews are posted by non-malicious users (Cai & Zhu, 2019) with different expectations as mentioned above. These actions by malicious or non-malicious users can negatively influence the quality (Chung et al., 2013; Singh et al., 2022; Yang et al., 2018), accuracy (Moradi & Hamidi, 2023; Xu et al., 2022; Yang et al., 2018) and, customers' trust (Aghili et al., 2011; Yang & Cai, 2017) of the recommendations provided which would pose risks causing customers to purchase inappropriate products (Cai & Zhu, 2019; Huang et al., 2021) and endure negative user experiences (Yang et al., 2018; Zeng et al., 2021).

The frequency of privacy leakages (Chen, 2022; Ran et al., 2022; Rohden & Zeferino, 2022) has increased as e-commerce RS continue to collect a tremendous amount of customer data to provide better recommendations. Privacy is the ability of an individual to determine what data can be shared, and employ access control (Ram Mohan Rao et al., 2018). It is an enduring issue of for people within the e-commerce setup (Tran & Huh, 2023) and they trust e-commerce firms to keep their purchase and ratings confidential (Ben Horin & Tassa, 2021). Privacy leakages can take place when transmitting data within the RS (Li et al., 2021), transferring or selling them to third parties, or failing to provide the required level of physical security (Erkin et al., 2012; Li et al., 2021; Mican et al., 2020; Polat & Du, 2005; Yan & Tang, 2011).

Customers' personal information/preferences, online purchase records, and keywords can be employed to infer various sensitive information such as their financial status, shopping preferences, personal interests and concerns, gender, sexual inclinations, and political beliefs (Li et al., 2021; Mican et al., 2020; Ram Mohan Rao et al., 2018) violating their privacy (Ran et al., 2022). Further, researchers have also highlighted building customer profiles using customer purchasing data to facilitate price discrimination (Erkin et al., 2012; Polat & Du, 2005) and for unsolicited marketing activities (Yan & Tang, 2011). This suggests privacy violations could lead to negative user experiences in the form of price discrimination imposed on customers. The next section of the review elaborates the risk-generating events associated with customer biases/actions.

4.3 Customer biases/actions

At times, customers become the source of risk-generating activities (see Table 8 for a summary of these events). RS play a significant role in customer decision making in the e-commerce context as mentioned. However, there are diverse kinds of individual-level biases that could harm customers' welfare. For instance, researchers (Ahmed et al., 2022; Gopalachari, 2018; Wang et al., 2022) have shown that customers are subjected to the influence of the reviews, product ratings, and product decisions of other customers in making product decisions, which is referred to as 'social influence bias' or 'conformity bias'. These researchers have also observed that customers tend to make product decisions under the influence of certain emotional states or interests. Further, customers at times tend to favour products simply because they are ranked high (position bias) and/or to favour neighbouring/related products (neighbouring bias) to a target product (Gu et al., 2020). Hence, it is evident that individual-level biases can sometimes result in customers making poor product purchase decisions.

Personalised product recommendations depend on customers' feedback as their preferences (i.e., reviews and ratings) eventually become input data for subsequent recommendations provided to other customers (Adomavicius et al., 2013; Ahmed et al., 2022; Fabbri, 2022). At times product reviews provided by new customers are influenced by the order sequence in which existing online reviews are captured, which is referred to as 'sequential bias' (Eryarsoy & Piramuthu, 2014).

Biased purchase data and product reviews serving as explicit input data (Eryarsoy & Piramuthu, 2014) to e-commerce RS will further aggravate the problem of low-quality recommendations affecting the purchase experience of future customers (Ahmed et al., 2022; Gopalachari, 2018).

Risk-generating events	Source/s
Customers complying with the choices of other customers (conformity/social influence bias)	*Ahmed et al., 2022; Gopalachari, 2018; Wang et al., 2022*
Customers providing biased reviews on products are influenced by the order sequence in which existing online reviews are captured by a new customer (sequential bias)	*Eryarsoy & Piramuthu, 2014*
Customers' decision biases (irregularities in human decision making) e.g., the tendency to make decisions under certain emotional state and interests	*Ahmed et al., 2022; Gopalachari, 2018*
Customers contributing to data leakages	*Ram Mohan Rao et al., 2018; Yan & Tang, 2011*
Customers' tendency to favour a product simply because it is ranked high (position bias) or neighbouring/related items influencing click-through rate of a target item (neighbouring bias)	*Gu et al., 2020*
Customers' lack of awareness of how algorithms make product recommendations	*Chen, 2022*

Table 8: Summary of the risk-generating events (Customer biases/actions)

On many occasions, customers' lack of awareness leads to problems such as privacy issues as well: For instance, agreeing to online terms and conditions on e-commerce platforms without fully understanding the privacy statements. As a result, customers contribute to the privacy issues associated with e-commerce RS (Ram Mohan Rao et al., 2018). To receive personalised recommendations, it is important to provide personal information each time a customer visits a new e-commerce platform. As a result of this, the more websites customers visit, the more personal information is disclosed which would result in increased privacy risks (Yan & Tang, 2011). In addition to that Chen (2022) has identified customers' general lack of awareness on how algorithms in e-commerce RS arrive at product recommendations (i.e., algorithmic opacity) as a challenge. Milano et al. (2020) have opined that providing transparent explanations on why a certain product is recommended to customers will enhance the transparency in the algorithmic decisions. This suggests that the presence of algorithmic opacity might lead customers to make uninformed product decisions which could lead to poor purchase decision risks. The next section of the review details the risk-generating events associated with incompetent e-commerce RS.

4.4 Incompetent systems

Incompetencies associated with e-commerce RS identified in this review are non-consideration of complex user requirements, information overload, and not capturing changing user preferences (see Table 9 for a summary). According to Vučetić and Hudec (2018), customers are often not able to express their requirements (i.e., expectations of specific features) in a precise way when inputting their preferences into an e-commerce RS. On the other hand, information overload is caused by overabundance of products, varieties of comparable products, and overload of related information. Such occurrence might lead customers to see the RS as incompetent and to either decline the recommendations or switch to another company (Kim et al., 2016). Similarly, Dou et al. (2021) have highlighted that users' interests and emotions (user bias) and their attraction towards specific products (item bias) might change over time. For example, a movie may gain attention when more information related to it becomes known (i.e., item bias). User biases occur in situations where a user's emotions play an important part in reviewing and rating products. According to Dou et al. (2021) collaborative filtering-based RS which rely on past information about user preferences to suggest personalised recommendations are not capable of identifying these kinds of changing preferences referred to as 'temporal changes'. The technology to capture changing preferences is gradually developing with the incorporation of deep learning algorithms, but there is still room for further improvement. Identifying such temporal changes is an essential aspect of providing effective personalised recommendations to customers and a failure to do so would result in a negative experience for customers. The next section presents the risk framework developed based on the potential links between risk-generating events and risks which were identified through this review.

Risk-generating events	Source/s
Incompetent recommender systems with functional issues (i.e., non-consideration of complex user requirements, information overload etc.)	*Kim et al., 2017; Vučetić & Hudec, 2018*
RS not capturing changing user preferences of products over time (user and item bias)	*Dou et al., 2021*

Table 9: Summary of the risk-generating events (Incompetent systems)

4.5 Risk framework for e-commerce RS

As stated, this review's purpose was to identify the full range of risk-generating events associated with e-commerce RS to overcome the limitations associated with existing risk classifications. In doing so, the link between the identified risk-generating events and the risks was elaborated with reference to the risk classification proposed by Jannach and Bauer (2020). The authors identified direct and indirect links between events and risks in the literature reviewed (see Table A 3 in Appendix). Risk-generating events identified under the category of 'biased recommendations': biased product recommendations, presenting incomplete or selective information, influencing customer preference ratings, lack of serendipity and/or diversity, use of biased visual properties, and biased exposure policy were identified as leading to poor decision risk and bad user experience risk. All these events pose the risk of customers purchasing products that are not suitable for their requirements with the associated risk of negatively affecting their shopping experience.

The second category 'malicious activities' encapsulated risk-generating events resulting from undesired human involvement in the recommendation process. These events overall are linked to all three types of risks: poor decision risk, bad user experience risk, and privacy risks. Dishonest ratings by malicious (i.e., shilling/profile injection attacks) as well as non-malicious users and review plagiarism might mislead customers to make poor purchase decisions as well as creating negative user experience. Unsolicited use of customer information certainly has implications for the privacy risks and issues. e.g., such as using customer information for unsolicited marketing activities might result in risk of bad user experience.

The third category of 'customer biases/actions' covered instances where customers themselves become the source of risk-generating events. They comprise conformity bias, sequential bias, irregularities in human decision-making, and customers contributing to data leakages. These events also have the potential to lead to all three types of risks. When customers are influenced by reviews and ratings provided by other customers, and positioning of product recommendations, or due to irregularities in human decision making they might end up making poor product choices. When biased reviews provided by customers act as explicit input data to RS, it will lead to providing low-quality product recommendations to other customers which will negatively affect their shopping experience. Agreeing to privacy statements without full understanding and exposing personal data on multiple platforms are instances where customers contribute to increased privacy risks. Issues associated with RS such as failure to capture complex user requirements, information overload, and failure to capture changing preferences would also lead to negative user experience with e-commerce RS. Based on this discussion, a risk framework is developed as shown in Figure 4.

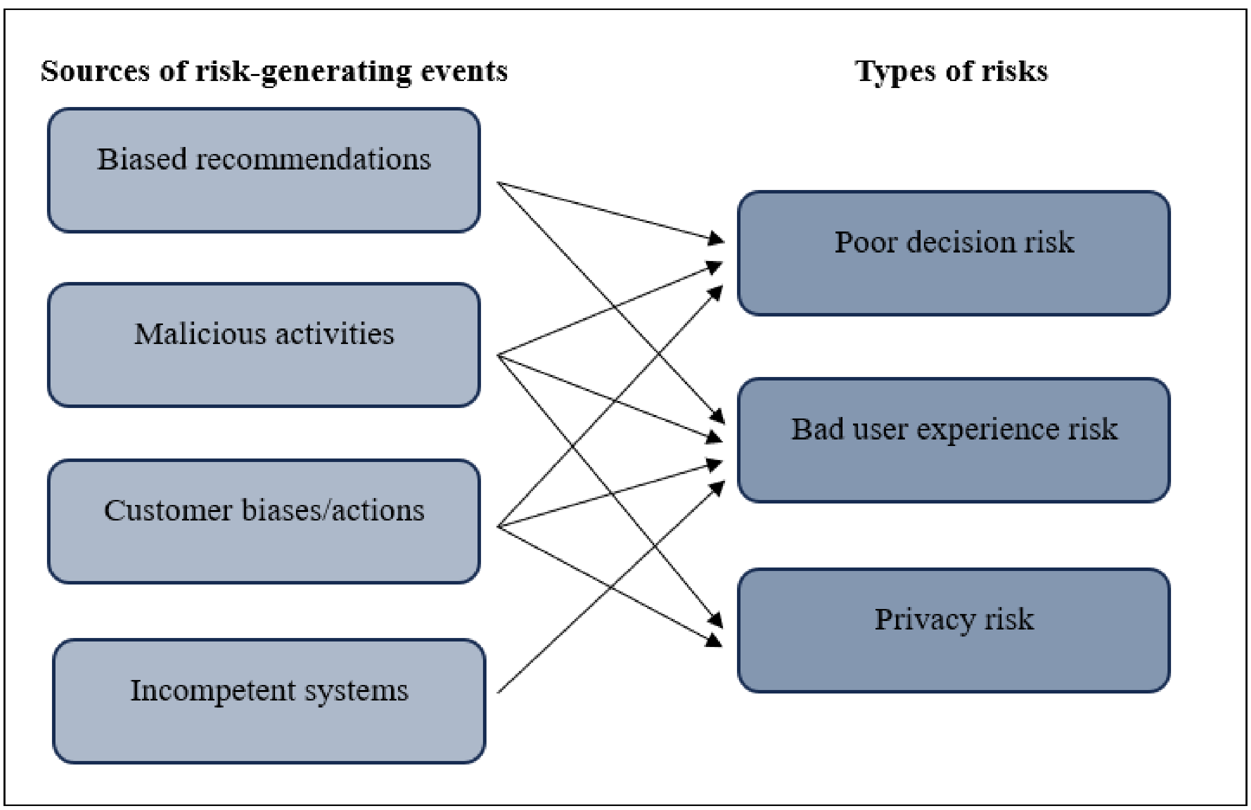

Figure 4: Risk framework for e-commerce RS

5 Discussion

The discussion consists of observations on the risks of e-commerce RS with reference to existing frameworks on risks, the impact of those risks on businesses, policy implications of risks, and limitations and directions for future research. Figure 5 summarizes the discussion presented below.

5.1 Observations on risks of e-commerce RS

Through this review, several risk-generating events that were not previously discussed with reference to e-commerce RS risks were identified. These events included profile injection attacks, review plagiarism, customer biases, and algorithmic opacity. This identification of novel risk-generating events is expected to provide a comprehensive view of the risk potential of current e-commerce RS. Further, the 'biased information state' which was originally proposed by Jannach and Bauer (2020) as a risk was identified as a source of several other types of biases (i.e., biased products, biased information, and biased marketing cues) associated with e-commerce RS. As mentioned before, these biases result in diverse types of risks such as poor decision risk and bad

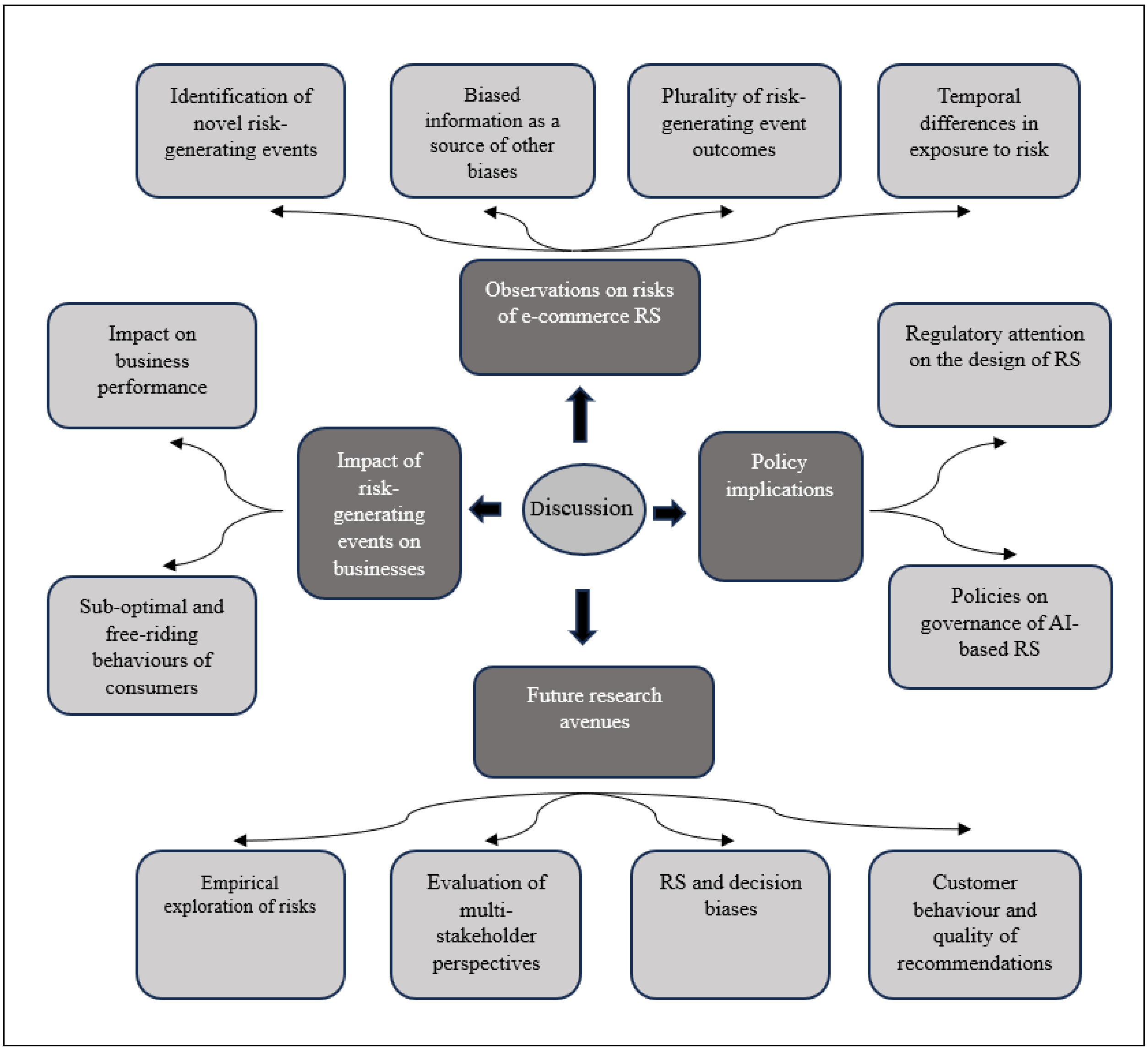

Figure 5 Summary of the discussion

user experience risk. Hence, the findings of this review suggest that the three types of risks poor decision risk, bad user experience risk, and privacy risk proposed by Jannach and Bauer better represent the risks of e-commerce RS (except biased information state risk). This is also in alignment with the risk classification proposed by Glover and Benbasat (2010) and re-affirms the comparison presented in Table 1.

A plurality in the outcomes of the risk-generating events was observed, where some of the risk-generating events identified were linked to multiple types of risks. For example, biased product recommendations were identified to have links to poor decision risk and bad user experience risk. Similarly, the actions of malicious users might lead to poor decision risk and bad user experience risk. However, in Glover and Benbasat's e-commerce risk framework, one unwanted event was always linked to one type of risk via the harm it causes. This indicates the potential for a novel approach to conceptualising risks associated with e-commerce RS.

A close examination of different risks indicates that there is a temporal difference in customers' exposure to risk. For example, a customer who receives biased recommendations might have a bad user experience at the time of searching for products/receiving recommendations. However, if the selected product does not meet his/her expectations then the risk of a poor decision would materialize only upon receiving/consuming the product. A similar idea has been presented by Milano et al. (2020) in their taxonomy of ethical challenges of RS, where they have identified some ethical challenges involving immediate harm or future exposure to risk. Within such a classification bad user experience will cause immediate harm, while poor decision risks and privacy risks create future exposure to risk. Next, the impact of identified risk-generating events on businesses is discussed.

5.2 Impact of risk-generating events on businesses

This review suggests that risk-generating events associated with e-commerce RS are detrimental to customers and businesses. For example, the decision to promote popular products might result in a negative user experience for customers and a long tail of unsold products which could result in a monetary loss for the business. On the other hand, when a company decides to promote unpopular products to increase catalogue coverage, the company might benefit from it in the short term, but customers will lose trust in the product recommendations provided to them. Interestingly Jannach and Bauer (2020) have highlighted these outcomes as organisational risks in their risk classifications of e-commerce RS (i.e., loss of customer trust, loss of societal trust, and monetary loss). This shows how the outcomes of risk-generating events affecting diverse stakeholders involved with e-commerce RS. This observation aligns with the multistakeholder perspective of RS (Abdollahpouri et al., 2020; Milano et al., 2020). RS are multistakeholder systems and in evaluating the impact of RS, the utility, rights, and risks of all stakeholders need to be considered (Milano et al., 2020). Accordingly, the generating events identified through this review provide an ideal avenue to identify the risks of e-commerce RS from the multistakeholder perspective.

Through this review, we were able to identify that the privacy issues associated with e-commerce RS led to several sub-optimal behaviours by customers: namely, not providing personal information (Rohden & Zeferino, 2022) and providing false information (Kashani & Hamidzadeh, 2020; Polat & Du, 2005). In addition, Nosi et al. (2022) have highlighted the free-riding behaviour of customers where they search for products online but buy products offline. In the case of incompetent or unreliable RS, some customers might decline recommendations received (Kim et al., 2017) and decide to stop purchasing from a particular e-commerce platform (Kim et al., 2017; Rohden & Zeferino, 2022). According to Eryarsoy and Piramuthu (2014), implicit and explicit data gathered via customer interactions are crucially important to provide effective recommendations. However, when customers avoid associating with e-commerce RS or engage in sub-optimal behaviours as mentioned above, it will affect the quantity and quality of information available to make effective personalised product recommendations. Hence, the risk-generating events associated with e-commerce RS could affect the business value of the RS. The next section explains the policy implications of the findings of this review.

5.3 Policy implications of the findings

Present-day e-commerce RS, that apply AI-based technologies can influence human decision-making related to products and services, which can have broader implications for society. For example, unhealthy food practices promoted by recommendations can burden the public health system (Fabbri, 2022). Due to these far-reaching implications, AI applications including RS have received policy-level attention from governments. The European Commission's regulatory framework on high-risk AI systems (European Commission, 2023) and the discussion paper published by the Australian government on mitigating potential risks of AI (Department of Industry, Science and Resources, Australia, 2023) are good examples of this.

Fabbri (2022) has identified that RS outputs are already being recognized under the European Commission's policy framework and highlights the need for incorporating the design principles due to the risks posed by biases in RS. In support of this view, Di Noia et al. (2022) have presented an account of how the issues unique to RS should be mitigated with reference to the European Commission's policy framework. In their work, they have looked at areas such as fairness, security, and privacy which are essential to mitigate the impact of certain risk-generating events that were discussed in this review. These scholars have consistently pointed out the inadequacy of existing policy frameworks in dealing with the negative effects associated with RS, especially with the use of AI in providing recommendations. According to Fabbri, existing design principles of RS can pose risks to users which has not received enough regulatory attention. In such a situation, enhanced understanding of diverse types of risk-generating events and risks associated with e-commerce RS would be helpful in contributing to the development of more robust policies and regulations to govern RS used in public domains, which will benefit society. The next section of the review presents the limitations and directions for future research.

5.4 Limitations and directions for future research

The publications selected for this review were limited to the last twenty years (from 2003 to 2023). We believe that we were able to identify a comprehensive range of risk-generating events as most publications on e-commerce RS were published during the last two decades. Only publications in the language of English were considered for this review. However, only a very minimal number of publications were excluded due to this reason. There are several future research avenues that emerge from this scoping review.

5.4.1 Empirical exploration of risks

The risk framework (Figure 4) is proposed based on the risk-generating events and their potential links to the risks as reported in the literature. Researchers can make use of the identified list of risk-generating events to empirically test their relationship with the risks of e-commerce RS. Such research will contribute towards updating and advancing the existing risk frameworks on e-commerce (e.g., Glover & Benbasat, 2010). Further, the proposed framework can be used to identify potential negative effects of Artificial Intelligence (AI) enabled e-commerce RS which has thus far received scant attention (Necula & Păvăloaia, 2023). In addition, the risk-generating events identified through this review can also be utilized to explore customers' risk perceptions of e-commerce RS by adopting the psychometric paradigm (Slovic, 1987). Such studies will help illuminate the theoretical understanding of e-commerce RS as a single hazard domain.

5.4.2 Evaluation of multistakeholder perspectives on e-commerce RS

During the conduct of this review, the authors were also able to identify that certain risk-generating events can affect multiple stakeholders involved with e-commerce RS. For instance, recommending popular products could lead to dissatisfaction for customers and at the same time lead to long-tail products which are a disadvantage for businesses. However, in our review, we could not identify any significant empirical evidence that looks at the risks of e-commerce RS from a multistakeholder perspective. However, scholars (Abdollahpouri et al., 2020; Jannach & Jugovac, 2019; Milano et al., 2020) in the recent past have advocated the need for further research on the impact of RS for different stakeholders to understand the trade-off between their expectations and the reality of the RS. Hence, the events identified in this study can be used as a basis to study how contradictory objectives are achieved by key stakeholders such as customers and businesses, as well as system developers.

5.4.3 RS and decision biases

The literature reviewed in this study has indicated diverse ways human decision biases come into effect when customers rely on e-commerce RS. This could result in irrational decisions which are sub-optimal in nature. Teppan and Zanker (2015) are of the opinion that customers should be equipped with the knowledge on decision biases so that they can make more objective decisions. In a recent review, Chen et al. (2023) have identified that in the real world context various biases could occur simultaneously. They advocate that the systems should be capable of handling multiple types of biases to enhance fairness and transparency in recommendations. At a time when there is heightened attention towards biases associated with RS, we believe the identification of specific biases and their potential links to risks discussed in this review should encourage researchers to further examine human decision biases associated with the use of e-commerce RS.

5.4.4 Customer behaviour and quality of recommendations

Customers engage in different sub-optimal and free-riding behaviour due to their lack of confidence and/or knowledge about RS (Kashani & Hamidzadeh, 2020; Nosi et al., 2022; Rohden & Zeferino, 2022). This could negatively affect e-commerce RS because the effectiveness of the recommendations provided depends on the accuracy of the information gathered from customers implicitly and explicitly (Eryarsoy & Piramuthu, 2014). Hence, it would be interesting to study the conditions under which customers engage in such behaviours. Findings on such specific conditions will be helpful to develop strategies to enhance customers' engagement with e-commerce RS (e.g., privacy-preserving capabilities of e-commerce RS). Such strategies could lead to an enhanced quality of personalised product recommendations provided by e-commerce RS to customers.

6 Conclusion

Risks associated with e-commerce RS have received significant attention from scholars and policymakers. A comprehensive understanding of the events leading to such risks is of crucial importance in identifying the risk potential of e-commerce RS. However, the lack of a comprehensive synthesis of the risk-generating events has hindered the advancement of scholarly discussion in this field. This review addressed this gap by identifying risk-generating events and corresponding risks associated with e-commerce RS from the customers' perspective as reported in the literature. Through this review, certain risk-generating events that were not considered in prior research for the conceptualisation of e-commerce risks were also identified. The findings of this review can be utilized to empirically examine risks and explore risk perceptions on e-commerce RS from a multistakeholder perspective. In addition to this, several other important future research directions stemming from the analysis were also suggested.

References

Abdollahpouri, H., Adomavicius, G., Burke, R., Guy, I., Jannach, D., Kamishima, T., Krasnodebski, J., & Pizzato, L. (2020). Multistakeholder recommendation: Survey and research directions. *User Modeling & User-Adapted Interaction*, *30*(1), 127–158. iih.

Adomavicius, G., Bockstedt, J. C., Curley, S. P., & Jingjing Zhang. (2013). Do Recommender Systems Manipulate Consumer Preferences? A Study of Anchoring Effects. *Information Systems Research*, *24*(4), 956–975. doi.org/10.1287/isre.2013.0497

Aghili, G., Shajari, M., Khadivi, S., & Morid, M. A. (2011). Using Genre Interest of Users to Detect Profile Injection Attacks in Movie Recommender Systems. *2011 10th International Conference on Machine Learning and Applications and Workshops*, *1*, 49–52. doi.org/10.1109/ICMLA.2011.151

Ahmed, A., Saleem, K., Khalid, O., Gao, J., & Rashid, U. (2022). Trust-aware denoising autoencoder with spatial-temporal activity for cross-domain personalized recommendations. *Neurocomputing*, *511*, 477–494. doi.org/10.1016/j.neucom.2022.09.023

Alamdari, P. M., Navimipour, N. J., Hosseinzadeh, M., Safaei, A. A., & Darwesh, A. (2020). A Systematic Study on the Recommender Systems in E-Commerce. *IEEE Access*, *8*, 115694–115716. doi.org/10.1109/ACCESS.2020.3002803

Awad, N. F., & Krishnan, M. S. (2006). The Personalization Privacy Paradox: An Empirical Evaluation of Information Transparency and the Willingness to Be Profiled Online for Personalization. *MIS Quarterly*, *30*(1), 13–28. doi.org/10.2307/25148715

Banker, S., & Khetani, S. (2019). Algorithm Overdependence: How the Use of Algorithmic Recommendation Systems Can Increase Risks to Consumer Well-Being. *Journal of Public Policy & Marketing*, *38*(4), 500–515. doi.org/10.1177/0743915619858057

Ben Horin, A., & Tassa, T. (2021). Privacy Preserving Collaborative Filtering by Distributed Mediation. *Fifteenth ACM Conference on Recommender Systems*, 332–341. doi.org/10.1145/3460231.3474251

Cai, Y., & Zhu, D. (2019). Trustworthy and profit: A new value-based neighbor selection method in recommender systems under shilling attacks. *Decision Support Systems*, *124*(C), 1–15. doi.org/10.1016/j.dss.2019.113112

Chen, Y. (2022). Analysis on the Impact of Recommender Systems on Consumer Decision: Making on China's Online Shopping Platforms. *2022 6th International Conference on E-Commerce, E-Business and E-Government*, 272–276. doi.org/10.1145/3537693.3537734

Chen, J., Dong, H., Wang, X., Feng, F., Wang, M., & He, X. (2023). Bias and Debias in Recommender System: A Survey and Future Directions. *ACM Transactions on Information Systems*, *41*(3), 1–39. doi.org/10.1145/3564284

Chevalier, S. (2024, May 22). Global retail e-commerce sales 2014-2027. Statista. https://www.statista.com/statistics/379046/worldwide-retail-e-commerce-sales/

Chopra, A. B., & Dixit, V. S. (2021). Balanced Accuracy of Collaborative Recommender System. *CT Systems and Sustainability: Proceedings of ICT4SD 2020*, *1*, 341–356. doi.org/10.1007/978-981-15-8289-9_32

Chopra, A. B., & Dixit, V. S. (2023). Detecting biased user-product ratings for online products using opinion mining. *Journal of Intelligent Systems*, *32*(1), 1–13. doi.org/10.1515/jisys-2022-9030

Chung, C. Y., Hsu, P. Y., & Huang, S. H. (2013). β P: A novel approach to filter out malicious rating profiles from recommender systems. *Decision Support Systems*, *55*(1), 314–325. doi.org/10.1016/j.dss.2013.01.020

David, S., & Pinch, T. (2006). View of Six degrees of reputation: The use and abuse of online review and recommendation systems. *First Monday*, *11*(3). https://doi.org/10.5210/fm.v11i3.1315

Deng, W., Shi, Y., Chen, Z., Kwak, W., & Tang, H. (2020). Recommender system for marketing optimization. *World Wide Web*, *23*(3), 1497–1517. doi.org/10.1007/s11280-019-00738-1

Department of Industry, Science and Resources, Australia. (2023). *Safe and responsible AI in Australia*. https://consult.industry.gov.au/supporting-responsible-ai

Di Noia, T., Tintarev, N., Fatourou, P., & Schedl, M. (2022). Recommender systems under European AI regulations. *Communications of the ACM*, *65*(4), 69–73. doi.org/10.1145/3512728

Dou, R., Arslan, O., & Zhang, C. (2021). Biased autoencoder for collaborative filtering with temporal signals. *Expert Systems with Applications*, *186*, 115775. doi.org/10.1016/j.eswa.2021.115775

Ebrahimi, S., Ghasemaghaei, M., & Benbasat, I. (2022). The Impact of Trust and Recommendation Quality on Adopting Interactive and Non-Interactive Recommendation Agents: A Meta-Analysis. *Journal of Management Information Systems*, *39*(3), 733–764. doi.org/10.1080/07421222.2022.2096549

Erkin, Z., Beye, M., Veugen, T., & Lagendijk, R. L. (2012). Privacy-preserving content-based recommender system. *Proceedings of the on Multimedia and Security*, 77–84. doi.org/10.1145/2361407.2361420

Eryarsoy, E., & Piramuthu, S. (2014). Experimental evaluation of sequential bias in online customer reviews. *Information & Management*, *51*(8), 964–971. iih. doi.org/10.1016/j.im.2014.09.001

Eslami, M., Vaccaro, K., Lee, M. K., Elazari Bar On, A., Gilbert, E., & Karahalios, K. (2019). User Attitudes towards Algorithmic Opacity and Transparency in Online Reviewing Platforms. *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*, 1–14. doi.org/10.1145/3290605.3300724

European Commission. (2023). *Regulatory framework proposal on artificial intelligence | Shaping Europe's digital future*. https://digital-strategy.ec.europa.eu/en/policies/regulatory-framework-ai

Fabbri, M. (2022). Social influence for societal interest: A pro-ethical framework for improving human decision making through multi-stakeholder recommender systems. *AI & Society*, *38*(2), 995–1002. doi.org/10.1007/s00146-022-01467-2

Felfernig, A. (2014). *Biases in Decision Making*. International Workshop on Decision Making and Recommender Systems, Bolzano, Italy. https://ceur-ws.org/Vol-1278/paper6.pdf

Fleder, D., & Hosanagar, K. (2009). Blockbuster Culture's Next Rise or Fall: The Impact of Recommender Systems on Sales Diversity. *Management Science*, *55*(5), 697–712. doi.org/10.1287/mnsc.1080.0974

Frey, R., Wörner, D., & Ilic, A. (2016). *Collaborative Filtering on the Blockchain: A Secure Recommender System for e-Commerce*. Twenty-second Americas Conference on Information Systems (AMCIS), San Diego, CA, USA. https://aisel.aisnet.org/amcis2016/ISSec/Presentations/36/

Ge, Y., Zhao, S., Zhou, H., Pei, C., Sun, F., Ou, W., & Zhang, Y. (2020). Understanding Echo Chambers in E-commerce Recommender Systems. *Proceedings of the 43rd International ACM SIGIR Conference on Research and Development in Information Retrieval*, 2261–2270. doi.org/10.1145/3397271.3401431

Glover, S., & Benbasat, I. (2010). A Comprehensive Model of Perceived Risk of E-Commerce Transactions. *International Journal of Electronic Commerce*, *15*(2), 47–78. https://doi-org.ezproxy.massey.ac.nz/10.2753/JEC1086-4415150202

Gopalachari, M. (2018). DBT Recommender: Improved Trustworthiness of Ratings through De-Biasing Tendency of Users. *International Journal of Intelligent Engineering and Systems*, *11*(2), 85–92. doi.org/10.22266/ijies2018.0430.10

Grange, C., Benbasat, I., & Burton-Jones, A. (2019). With a little help from my friends: Cultivating serendipity in online shopping environments. *Information & Management*, *56*(2), 225–235. doi.org/10.1016/j.im.2018.06.001

Grant, M. J., & Booth, A. (2009). A typology of reviews: an analysis of 14 review types and associated methodologies. *Health information & libraries journal*, *26*(2), 91-108.

Gu, Y., Ding, Z., Wang, S., Zou, L., Liu, Y., & Yin, D. (2020). Deep Multifaceted Transformers for Multi-objective Ranking in Large-Scale E-commerce Recommender Systems. *Proceedings of the 29th ACM International Conference on Information & Knowledge Management*, 2493–2500. doi.org/10.1145/3340531.3412697

He, F., Wang, X., & Liu, B. (2010). Attack Detection by Rough Set Theory in Recommendation System. *2010 IEEE International Conference on Granular Computing*, 692–695. doi.org/10.1109/GrC.2010.130

Ho, Y.-C. (Chad), Wu, J., & Tan, Y. (2017). Disconfirmation Effect on Online Rating Behavior: A Structural Model. *Information Systems Research*, *28*(3), 626–642.

Hsieh, C. L. (2011). Toward Better Recommender System by Collaborative Computation with Privacy Preserved. *2011 IEEE/IPSJ International Symposium on Applications and the Internet*, 246–249. doi.org/10.1109/SAINT.2011.46

Hu, L., Cao, L., Cao, J., Gu, Z., Xu, G., & Wang, J. (2017). Improving the Quality of Recommendations for Users and Items in the Tail of Distribution. *ACM Transactions on Information Systems*, *35*(3), 1–37. doi.org/10.1145/3052769

Huang, J. T., Sun, H. L., Chen, X. F., Liu, X., & Cao, J. (2021). An Iterative Deviation-based Ranking Method to Evaluate User Reputation in Online Rating Systems∗. *2021 4th International Conference on Data Science and Information Technology*, 15–21. doi.org/10.1145/3478905.3478909

Jannach, D., & Bauer, C. (2020). Escaping the McNamara Fallacy: Toward More Impactful Recommender Systems Research. *AI Magazine*, *41*(4), 79–95. doi.org/10.1609/aimag.v41i4.5312

Jannach, D., & Jugovac, M. (2019). Measuring the Business Value of Recommender Systems. *ACM Transactions on Management Information Systems*, *10*(4), 1–23. doi.org/10.1145/3370082

Jannach, D., Pu, P., Ricci, F., & Zanker, M. (2022). Recommender systems: Trends and frontiers. *AI Magazine*, *43*(2), 145–150. doi.org/10.1002/aaai.12050

Jannach, D., Zanker, M., Ge, M., & Gröning, M. (2012). Recommender Systems in Computer Science and Information Systems – A Landscape of Research. *E-Commerce and Web Technologies*, *123*, 76–87. doi.org/10.1007/978-3-642-32273-0_7

Jeyamohan, N., Chen, X., & Aslam, N. (2019). Local Differentially Private Matrix Factorization for Recommendations. *2019 13th International Conference on Software, Knowledge, Information Management and Applications (SKIMA)*, 1–5. doi.org/10.1109/SKIMA47702.2019.8982536

Kashani, S. M. Z., & Hamidzadeh, J. (2020). Feature selection by using privacy-preserving of recommendation systems based on collaborative filtering and mutual trust in social networks. *Soft Computing*, *24*(15), 11425–11440. doi.org/10.1007/s00500-019-04605-z

Kim, H., Benbasat, I., & Cavusoglu, H. (2017). Online Consumers' Attribution of Inconsistency Between Advice Sources. *ICIS 2017 Proceedings*, 1–10. https://www.proceedings.com/37640.html

Kiswanto, D., Nurjanah, D., & Rismala, R. (2018). Fairness Aware Regularization on a Learning-to-Rank Recommender System for Controlling Popularity Bias in E-Commerce Domain. *2018 International Conference on Information Technology Systems and Innovation (ICITSI)*, 16–21. doi.org/10.1109/ICITSI.2018.8696023

Kong, D., Tang, J., Zhu, Z., Cheng, J., & Zhao, Y. (2017). De-biased dart ensemble model for personalized recommendation. *2017 IEEE International Conference on Multimedia and Expo (ICME)*, 553–558. doi.org/10.1109/ICME.2017.8019536

Kumar, A., Garg, D., & Rana, P. S. (2015). Ensemble approach to detect profile injection attack in recommender system. *2015 International Conference on Advances in Computing, Communications and Informatics (ICACCI)*, 1734–1740. doi.org/10.1109/ICACCI.2015.7275864

Laskar, A. K., Ahmed, J., Sohail, S. S., Nafis, A., & Haq, Z. A. (2023). Shilling Attacks on Recommender System: A Critical Analysis. *10th International Conference on Computing for Sustainable Global Development (INDIACom)*, 1617–1622. https://ieeexplore-ieee-org.ezproxy.massey.ac.nz/document/10112342

Lee, D., & Hosanagar, K. (2019). How Do Recommender Systems Affect Sales Diversity? A Cross-Category Investigation via Randomized Field Experiment. *Information Systems Research*, *30*(1), 239–259. doi.org/10.1287/isre.2018.0800

Lee, Y. H., Hu, P. J. H., Cheng, T. H., & Hsieh, Y. F. (2012). A cost-sensitive technique for positive-example learning supporting content-based product recommendations in B-to-C e-commerce. *Decision Support Systems*, *53*(1), 245–256. doi.org/10.1016/j.dss.2012.01.018

Li, G., Yin, G., Yang, J., & Chen, F. (2021). SDRM-LDP: A Recommendation Model Based on Local Differential Privacy. *Wireless Communications and Mobile Computing*, 2021, 1–15. doi.org/10.1155/2021/6640667

Li, S., & Karahanna, E. (2015). Online Recommendation Systems in a B2C E-Commerce Context: A Review and Future Directions. *Journal of the Association for Information Systems*, *16*(2), 72–107. doi.org/10.17705/1jais.00389

Lu, Z., & Shen, H. (2015). An Accuracy-Assured Privacy-Preserving Recommender System for Internet Commerce. *Computer Science and Information Systems*, *12*(4), 1307–1326. doi.org/10.2298/CSIS140725056L

Mallik, S., & Sahoo, A. (2020). A Comparison Study of Different Privacy Preserving Techniques in Collaborative Filtering Based Recommender System. *Computational Intelligence in Data Mining*, 193–203. doi.org/10.1007/978-981-13-8676-3_17

Mican, D., Sitar-Tăut, D. A., & Moisescu, O. I. (2020). Perceived usefulness: A silver bullet to assure user data availability for online recommendation systems. *Decision Support Systems*, *139*, 113420. doi.org/10.1016/j.dss.2020.113420

Milano, S., Taddeo, M., & Floridi, L. (2020). Recommender systems and their ethical challenges. *AI & SOCIETY*, *35*(4), 957–967. doi.org/10.1007/s00146-020-00950-y

Moradi, R., & Hamidi, H. (2023). A New Mechanism for Detecting Shilling Attacks in Recommender Systems Based on Social Network Analysis and Gaussian Rough Neural Network with Emotional Learning. *International Journal of Engineering*, *36*(2), 321–334. doi.org/10.5829/IJE.2023.36.02B.12

Munn, Z., Peters, M. D. J., Stern, C., Tufanaru, C., McArthur, A., & Aromataris, E. (2018). Systematic review or scoping review? Guidance for authors when choosing between a systematic or scoping review approach. *BMC Medical Research Methodology*, *18*(1), 143. doi.org/10.1186/s12874-018-0611-x

Murphy, M. S. (2011). Notes toward a politics of personalization. *Proceedings of the 2011 iConference*, 546–551. doi.org/10.1145/1940761.1940836

Necula, S. C., & Păvăloaia, V. D. (2023). AI-Driven Recommendations: A Systematic Review of the State of the Art in E-Commerce. *Applied Sciences*, *13*(9), 5531. doi.org/10.3390/app13095531

Niu, K., Zhao, X., Li, F., Li, N., Peng, X., & Chen, W. (2019). UTSP: User-Based Two-Step Recommendation With Popularity Normalization Towards Diversity and Novelty. *IEEE Access, Access, IEEE*, *7*, 145426–145434. edseee. doi.org/10.1109/ACCESS.2019.2939945

Nosi, C., Zollo, L., Rialti, R., & Ciappei, C. (2022). Why do consumers free ride? Investigating the effects of cognitive effort on postpurchase dissonance. *Journal of Consumer Marketing*, *39*(5), 417–431. doi.org/10.1108/JCM-02-2021-4436

Nowell, L. S., Norris, J. M., White, D. E., & Moules, N. J. (2017). Thematic Analysis: Striving to Meet the Trustworthiness Criteria. *International Journal of Qualitative Methods*, *16*(1), 1609406917733847. doi.org/10.1177/1609406917733847

Panniello, U., Hill, S., & Gorgoglione, M. (2016). The impact of profit incentives on the relevance of online recommendations. *Electronic Commerce Research and Applications*, *20*, 87–104. doi.org/10.1016/j.elerap.2016.10.003

Peters, M. D. J., Godfrey, C. M., Khalil, H., McInerney, P., Parker, D., & Soares, C. B. (2015). Guidance for conducting systematic scoping reviews. *International Journal of Evidence-Based Healthcare*, *13*(3), 141–146. doi.org/10.1097/XEB.0000000000000050

Pizzato, L., Rej, T., Akehurst, J., Koprinska, I., Yacef, K., & Kay, J. (2013). Recommending people to people: The nature of reciprocal recommenders with a case study in online dating. *User Modeling & User-Adapted Interaction*, *23*(5), 447–488. iih.

Polat, H., & Du, W. (2005). Privacy-Preserving Collaborative Filtering. *International Journal of Electronic Commerce*, *9*(4), 9–35. doi.org/10.1080/10864415.2003.11044341

Puntoni, S., Reczek, R. W., Giesler, M., & Botti, S. (2021). Consumers and Artificial Intelligence: An Experiential Perspective. *Journal of Marketing*, *85*(1), 131–151. doi.org/10.1177/0022242920953847

Qiu, J., Lin, Z., & Li, Y. (2015). Predicting customer purchase behavior in the e-commerce context. *Electronic Commerce Research*, *15*(4), 427–452. doi.org/10.1007/s10660-015-9191-6

Qiu, R., Wang, S., Chen, Z., Yin, H., & Huang, Z. (2021). CausalRec: Causal Inference for Visual Debiasing in Visually-Aware Recommendation. *Proceedings of the 29th ACM International Conference on Multimedia*, 3844–3852. doi.org/10.1145/3474085.3475266

Ram Mohan Rao, P., Murali Krishna, S., & Siva Kumar, A. P. (2018). Privacy preservation techniques in big data analytics: A survey. *Journal of Big Data*, *5*(1), 33. doi.org/10.1186/s40537-018-0141-8

Ran, X., Wang, Y., Zhang, L. Y., & Ma, J. (2022). A differentially private matrix factorization based on vector perturbation for recommender system. *Neurocomputing*, *483*, 32–41. doi.org/10.1016/j.neucom.2022.01.079

Rohden, S. F., & Zeferino, D. G. (2022). Recommendation agents: An analysis of consumers' risk perceptions toward artificial intelligence. *Electronic Commerce Research*. doi.org/10.1007/s10660-022-09626-9

Silva, N., Carvalho, D., Pereira, A. C. M., Mourão, F., & Rocha, L. (2019). The Pure Cold-Start Problem: A deep study about how to conquer first-time users in recommendations domains. *Information Systems*, *80*, 1–12. doi.org/10.1016/j.is.2018.09.001

Singh, P. K., Pramanik, P. K. D., Sardar, M., Nayyar, A., Masud, M., & Choudhury, P. (2022). Generating A New Shilling Attack for Recommendation Systems. *Computers, Materials & Continua*, *71*(2), 2827–2846. doi.org/10.32604/cmc.2022.020437

Smith, B., & Linden, G. (2017). Two Decades of Recommender Systems at Amazon.com. *IEEE Internet Computing*, *21*(3), 12–18. doi.org/10.1109/MIC.2017.72

Slovic, P. (1987). Perception of Risk. *Science*, *236*(4799). doi.org/10.1126/science.3563507

Sreepada, R. S., & Patra, B. K. (2021). Enhancing long tail item recommendation in collaborative filtering: An econophysics-inspired approach. *Electronic Commerce Research and Applications*, *49*, 1–11. doi.org/10.1016/j.elerap.2021.101089

Teppan, E. C., & Zanker, M. (2015). Decision Biases in Recommender Systems. *Journal of Internet Commerce*, *14*(2), 255–275. doi.org/10.1080/15332861.2015.1018703

Tiihonen, J., & Felfernig, A. (2017). An introduction to personalization and mass customization. *Journal of Intelligent Information Systems*, *49*(1), 1–7. doi.org/10.1007/s10844-017-0465-4

Trakulwaranont, D., Kastner, M. A., & Satoh, S. (2022). Personalized Fashion Recommendation Using Pairwise Attention. *MultiMedia Modeling*, 218–229. doi.org/10.1007/978-3-030-98355-0_19

Tran, D. T., & Huh, J. H. (2023). Forecast of seasonal consumption behavior of consumers and privacy-preserving data mining with new S-Apriori algorithm. *The Journal of Supercomputing*, *79*, 12691–12736. doi.org/10.1007/s11227-023-05105-6

Tricco, A. C., Lillie, E., Zarin, W., O'Brien, K. K., Colquhoun, H., Levac, D., Moher, D., Peters, M. D. J., Horsley, T., Weeks, L., Hempel, S., Akl, E. A., Chang, C., McGowan, J., Stewart, L., Hartling, L., Aldcroft, A., Wilson, M. G., Garritty, C., … Straus, S. E. (2018). PRISMA Extension for Scoping Reviews (PRISMA-ScR): Checklist and Explanation. *Annals of Internal Medicine*, *169*(7), 467–473. doi.org/10.7326/M18-0850

Vailati Riboni, F., Comazzi, B., Bercovitz, K., Castelnuovo, G., Molinari, E., & Pagnini, F. (2020). Technologically - enhanced psychological interventions for older adults: A scoping review. *BMC Geriatrics*, *20*(1), 191. doi.org/10.1186/s12877-020-01594-9

Vučetić, M., & Hudec, M. (2018). A fuzzy query engine for suggesting the products based on conformance and asymmetric conjunction. *Expert Systems with Applications*, *101*, 143–158. doi.org/10.1016/j.eswa.2018.01.049

Wan, M., Ni, J., Misra, R., & McAuley, J. (2020). Addressing Marketing Bias in Product Recommendations. *Proceedings of the 13th International Conference on Web Search and Data Mining*, 618–626. doi.org/10.1145/3336191.3371855

Wang, H., Wang, Z., & Zhang, W. (2018). Quantitative analysis of Matthew effect and sparsity problem of recommender systems. *2018 IEEE 3rd International Conference on Cloud Computing and Big Data Analysis (ICCCBDA)*, 78–82. doi.org/10.1109/ICCCBDA.2018.8386490

Wang, W., Xu, J. (David), & Wang, M. (2018). Effects of Recommendation Neutrality and Sponsorship Disclosure on Trust vs. Distrust in Online Recommendation Agents: Moderating Role of Explanations for Organic Recommendations. *Management Science*, *64*(11), 5198–5219. doi.org/10.1287/mnsc.2017.2906

Wang, Y., Ma, W., Zhang, M., Liu, Y., & Ma, S. (2023). A Survey on the Fairness of Recommender Systems. *ACM Transactions on Information Systems*, *41*(3), 52:1-52:43. doi.org/10.1145/3547333

Wang, Z., He, Y., Liu, J., Zou, W., Yu, P. S., & Cui, P. (2022). Invariant Preference Learning for General Debiasing in Recommendation. *Proceedings of the 28th ACM SIGKDD Conference on Knowledge Discovery and Data Mining*, 1969–1978. doi.org/10.1145/3534678.3539439

Wei, R., & Shen, H. (2016). An Improved Collaborative Filtering Recommendation Algorithm against Shilling Attacks. *2016 17th International Conference on Parallel and Distributed Computing, Applications and Technologies (PDCAT)*, 330–335. doi.org/10.1109/PDCAT.2016.077

Wilson, R. S., Zwickle, A., & Walpole, H. (2019). Developing a Broadly Applicable Measure of Risk Perception. *Risk Analysis*, *39*(4), 777–791. doi.org/10.1111/risa.13207

Xiao, B., & Benbasat, I. (2014). Research on the Use, Characteristics, and Impact of e-Commerce Product Recommendation Agents: A Review and Update for 2007–2012. In *Handbook of Strategic e-Business Management* (pp. 403–431). Springer. doi.org/10.1007/978-3-642-39747-9_18

Xiao, B., & Benbasat, I. (2015). Designing Warning Messages for Detecting Biased Online Product Recommendations: An Empirical Investigation. *Information Systems Research*, *26*(4), 793–811. EDSWSS. doi.org/10.1287/isre.2015.0592

Xiao, B., & Benbasat, I. (2018). An empirical examination of the influence of biased personalized product recommendations on consumers' decision making outcomes. *Decision Support Systems*, *110*, 46–57. doi.org/10.1016/j.dss.2018.03.005

Xiao, B. S., & Tan, C.W. (2012). Reducing perceived deceptiveness of e-commerce product recommendation agents: An empirical examination of the relative impact of transparency and verifiability and the moderating role of gender. *AMCIS 2012 Proceedings*. Americas conference on information systems. https://aisel.aisnet.org/amcis2012/proceedings/HCIStudies/28

Xiao, Pei, Q., Yao, L., & Wang, X. (2020). RecRisk: An enhanced recommendation model with multi-facet risk control. *Expert Systems with Applications*, *158*, 113561. doi.org/10.1016/j.eswa.2020.113561

Xin, X., Yang, J., Wang, H., Ma, J., Ren, P., Luo, H., Shi, X., Chen, Z., & Ren, Z. (2023). On the User Behavior Leakage from Recommender System Exposure. *ACM Transactions on Information Systems*, *41*(3), 1–25. doi.org/10.1145/3568954

Xu, Y., Yang, Y., Wang, E., Zhuang, F., & Xiong, H. (2022). Detect Professional Malicious User With Metric Learning in Recommender Systems. *IEEE Transactions on Knowledge and Data Engineering*, *34*(9), 4133–4146. doi.org/10.1109/TKDE.2020.3040618

Yan, C. M., & Tang, T. J. (2011). Applying customer-centered recommendation on an on-line shopping system. *2011 Seventh International Conference on Natural Computation*, *4*, 1993–1997. doi.org/10.1109/ICNC.2011.6022582

Yang, Z., & Cai, Z. (2017). Detecting abnormal profiles in collaborative filtering recommender systems. *Journal of Intelligent Information Systems*, *48*(3), 499–518. doi.org/10.1007/s10844-016-0424-5

Yang, Z., Sun, Q., & Zhang, B. (2018). Evaluating Prediction Error for Anomaly Detection by Exploiting Matrix Factorization in Rating Systems. *IEEE Access*, *6*, 50014–50029. doi.org/10.1109/ACCESS.2018.2869271

Zeng, T., Fang, X., Lang, Y., Peng, J., Wu, X., Wang, S., & Gong, J. (2021). Fair Personalized Recommendation through Improved Matrix Factorization by Neural Networks. *2021 The 10th International Conference on Networks, Communication and Computing*, 19–24. doi.org/10.1145/3510513.3510517

Zhang, F. G., & Sheng-hua, X. (2007). Analysis of trust-based e-commerce recommender systems under recommendation attacks. *The First International Symposium on Data, Privacy, and E-Commerce (ISDPE 2007,)* 385-390. doi.org/10.1109/ISDPE.2007.75

Appendix 1

No.	Journal Title	Year of Publication	Publication Outlet
1	Ensemble approach to detect profile injection attack in recommender system	2015	2015 International Conference on Advances in Computing, Communications and Informatics, ICACCI 2015
2	Fairness Aware Regularization on a Learning-to-Rank Recommender System for Controlling Popularity Bias in E-Commerce Domain	2018	2018 International Conference on Information Technology Systems and Innovation, ICITSI 2018 - Proceedings
3	Local Differentially Private Matrix Factorization For Recommendations	2019	2019 13th International Conference on Software, Knowledge, Information Management and Applications, SKIMA 2019
4	An Iterative Deviation-based Ranking Method to Evaluate User Reputation in Online Rating Systems	2021	ACM International Conference Proceeding Series
5	Analysis on the Impact of Recommender Systems on Consumer Decision Making on China's Online Shopping Platforms	2022	
6	Fair Personalized Recommendation through Improved Matrix Factorization by Neural Networks	2021	
7	Improving the Quality of Recommendations for Users and Items in the Tail of Distribution	2017	ACM Transactions on Information Systems
8	A Comparison Study of Different Privacy Preserving Techniques in Collaborative Filtering Based Recommender System	2020	Advances in Intelligent Systems and Computing
9	Balanced Accuracy of Collaborative Recommender System.	2021	
10	Social influence for societal interest: a pro-ethical framework for improving human decision making through multi-stakeholder recommender systems	2022	AI and Society
11	Collaborative Filtering on the Blockchain: A Secure Recommender System for e-Commerce	2016	AMCIS 2016: Surfing the IT Innovation Wave - 22nd Americas Conference on Information Systems
12	An Accuracy-Assured Privacy-Preserving Recommender System for Internet Commerce	2015	Computer Science & Information Systems
13	Generating A New Shilling Attack for Recommendation Systems	2022	Computers, Materials & Continua
14	A cost-sensitive technique for positive-example learning supporting content-based product recommendations in B-to-C e-commerce	2012	Decision Support Systems

15	An empirical examination of the influence of biased personalized product recommendations on consumers' decision making outcomes	2018	
16	Perceived usefulness: A silver bullet to assure user data availability for online recommendation systems	2020	Decision Support Systems
17	Trustworthy and profit: A new value-based neighbor selection method in recommender systems under shilling attacks	2019	
18	β P : A novel approach to filter out malicious rating profiles from recommender systems	2013	
19	Recommendation agents: an analysis of consumers' risk perceptions toward artificial intelligence	2022	Electronic Commerce Research
20	Enhancing long tail item recommendation in collaborative filtering: An econophysics-inspired approach	2021	Electronic Commerce Research & Applications
21	The impact of profit incentives on the relevance of online recommendations	2016	
22	A fuzzy query engine for suggesting the products based on conformance and asymmetric conjunction	2018	Expert Systems with Applications
23	Biased autoencoder for collaborative filtering with temporal signals	2021	
24	RecRisk: An enhanced recommendation model with multi-facet risk control | Elsevier Enhanced Reader	2020	
25	View of Six degrees of reputation: The use and abuse of online review and recommendation systems	2006	First Monday
26	Online Consumers' Attribution of Inconsistency Between Advice Sources	2017	ICIS 2017: Transforming Society with Digital Innovation
27	A Systematic Study on the Recommender Systems in the E-Commerce	2017	IEEE Access
28	Evaluating Prediction Error for Anomaly Detection by Exploiting Matrix Factorization in Rating Systems	2018	
29	UTSP: User-Based Two-Step Recommendation With Popularity Normalization Towards Diversity and Novelty	2019	
30	Detect Professional Malicious User With Metric Learning in Recommender Systems	2022	IEEE Transactions on Knowledge and Data Engineering
31	Experimental evaluation of sequential bias in online customer reviews	2014	Information & Management

32	With a little help from my friends: Cultivating serendipity in online shopping environments	2019	
33	The Pure Cold-Start Problem: A deep study about how to conquer first-time users in recommendations domains	2019	Information Systems
34	Designing Warning Messages for Detecting Biased Online Product Recommendations: An Empirical Investigation	2015	Information Systems Research
35	Do Recommender Systems Manipulate Consumer Preferences? A Study of Anchoring Effects	2013	
36	Deep Multifaceted Transformers for Multi-objective Ranking in Large-Scale E-commerce Recommender Systems	2020	International Conference on Information and Knowledge Management, Proceedings
37	Personalized Fashion Recommendation Using Pairwise Attention	2022	International Conference on Multimedia Modeling
38	Privacy-Preserving Collaborative Filtering	2005	International Journal of Electronic Commerce
39	A New Mechanism for Detecting Shilling Attacks in Recommender Systems Based on Social Network Analysis and Gaussian Rough Neural Network with Emotional Learning	2023	International Journal of Engineering Transactions C: Aspects
40	DBT Recommender: Improved Trustworthiness of Ratings through De-Biasing Tendency of Users	2018	International Journal of Intelligent Engineering and Systems
41	Privacy preservation techniques in big data analytics: a survey	2018	Journal of Big Data
42	Detecting abnormal profiles in collaborative filtering recommender systems	2017	Journal of Intelligent Information Systems
43	Detecting biased user-product ratings for online products using opinion mining	2023	Journal of Intelligent Systems
44	Blockbuster Culture's Next Rise or Fall: The Impact of Recommender Systems on Sales Diversity	2009	Management Science
45	Effects of Recommendation Neutrality and Sponsorship Disclosure on Trust vs. Distrust in Online Recommendation Agents: Moderating Role of Explanations for Organic Recommendations	2018	
46	CausalRec: Causal Inference for Visual Debiasing in Visually-Aware Recommendation	2021	MM 2021 - Proceedings of the 29th ACM International Conference on Multimedia
47	Privacy-preserving content-based recommender system	2012	MM and Sec'12 - Proceedings of the 14th ACM Multimedia and Security Workshop
48	A differentially private matrix factorization based on vector perturbation for recommender system	2022	Neurocomputing

49	Trust-aware denoising autoencoder with spatial-temporal activity for cross-domain personalized recommendations	2022	
50	An Improved Collaborative Filtering Recommendation Algorithm against Shilling Attacks	2016	Parallel and Distributed Computing, Applications and Technologies, PDCAT Proceedings
51	Using Genre Interest of Users to Detect Profile Injection Attacks in Movie Recommender Systems	2011	Proceedings - 10th International Conference on Machine Learning and Applications, ICMLA 2011
52	Toward Better Recommender System by Collaborative Computation with Privacy Preserved	2011	Proceedings - 11th IEEE/IPSJ International Symposium on Applications and the Internet, SAINT 2011
53	Attack Detection by Rough Set Theory in Recommendation System	2010	Proceedings - 2010 IEEE International Conference on Granular Computing, GrC 2010
54	Applying customer-centered recommendation on an on-line shopping system	2011	Proceedings - 2011 7th International Conference on Natural Computation, ICNC 2011
55	Analysis of Trust-Based E-Commerce Recommender Systems Under Recommendation Attacks	2007	Proceedings of the 1st International Symposium on Data, Privacy, and E-Commerce, ISDPE 2007
56	Invariant Preference Learning for General Debiasing in Recommendation	2022	Proceedings of the ACM SIGKDD International Conference on Knowledge Discovery and Data Mining
57	Privacy Preserving Collaborative Filtering by Distributed Mediation	2021	RecSys 2021 - 15th ACM Conference on Recommender Systems
58	Understanding Echo Chambers in E-commerce Recommender Systems	2020	SIGIR 2020 - Proceedings of the 43rd International ACM SIGIR Conference on Research and Development in Information Retrieval
59	Feature selection by using privacy-preserving of recommendation systems based on collaborative filtering and mutual trust in social networks	2020	Soft Computing
60	SDRM-LDP: A Recommendation Model Based on Local Differential Privacy	2021	Wireless Communications and Mobile Computing
61	Recommender system for marketing optimization	2020	World Wide Web
62	Addressing Marketing Bias in Product Recommendations	2020	WSDM 2020 - Proceedings of the 13th International Conference on Web Search and Data Mining

Table: A1 Selected publications and journal titles

Appendix 2:

Category	Risk-generating events	Outcomes	Source/s
Biased recommendations	Recommending popular products (popularity bias), less frequently purchased products, and/or ignoring unpopular/new/obscure products (long tail products)	Resulting in a "long tail" of unsold items in the product space and those items are not shown to customers; lack of diversity and novelty in the recommendations weakening customer experience; customers foregoing better customer-product matches; potential balkanization, herding (convergence of groups with similar interests); 'filters' creating a fragmented society; poor personalisation of recommendations to customers	*(Deng et al., 2020; Fleder & Hosanagar, 2009; Gu et al., 2020; Kiswanto et al., 2018; Lee et al., 2012; Niu et al., 2019; Sreepada & Patra, 2021; Vučetić & Hudec, 2018; Z. Wang et al., 2022; Zeng et al., 2021)*
	Presenting selective/incomplete information or hiding information	Incomplete or hidden information impairing user experience; influences on users' subjective comprehension of services which may lead to variations of personal preferences; negative impact on the accuracy of the RS	*(Kim et al., 2017; Xiao et al., 2020)*
	Promoting profitable products/un-profitable products	Users exploited by biased RS; users' distrust of RS when they are aware of recommendation biases; customers believing that the biased recommendations make product searching easier and recommended products are the best choice for them (affecting customers' decision quality and decision effort); negative impact on the credibility of the RS	*(Panniello et al., 2016; Wang et al., 2018; Xiao & Benbasat, 2015, 2018)*
	Use of biased/unbalanced user data to provide biased product recommendations to firs time/lesser-known customers	Unhelpful recommendations for rare occasions or lesser-known users; certain first-time users not being satisfied with the biased recommendations	*(Hu et al., 2017; Silva et al., 2019; Trakulwaranont et al., 2022)*
	Generating biased system ratings which influence subsequent customer preference ratings (anchoring effect)	The feedback loop between user-reported ratings and system-generated recommendations is affected (cascading error effect on the performance of the RS); anchoring effects biasing the inputs to RS; businesses using RS strategically for their	*(Adomavicius et al., 2013; Fabbri, 2022; Xiao & Benbasat, 2015)*

Category	Risk-generating events	Outcomes	Source/s
		competitive advantage (e.g., inventory management)	
	Lacking the surprise element (i.e., serendipity) and/or diversity in recommendations	Lack of shopper engagement and satisfaction; continued narrow exposure of items raised by RS resulting in an echo chamber (like-minded users/customers); recommendations making people isolated from diverse content (filter bubble); negative social outcomes of bad customer choices	*(Fabbri, 2022; Ge et al., 2020; Grange et al., 2019)*
	Presenting visually biased product recommendations and/or using biased marketing cues to promote products	Customers' dissatisfaction with other features (e.g., brand, material) leads to rejecting a product; underrepresentation of niche markets in the input data for a RS; customers struggling to find relevant products; potential ethical and social issues	*(Qiu et al., 2021; Wan et al., 2020)*
	Biased policies on exposing search results to customers (exposure bias)	Influence on users' purchase behaviour	*(Wang et al., 2022)*
Malicious activities	Shilling/ Profile injection attacks by malicious users	Users may unreasonably focus on brands with top scores leading to poor product choices; honest merchants may suffer excessive loss or even be driven to bankruptcy; investments in fake raters getting promoted; unfair treatment of both users and merchants leading to market disorder; decreasing the accuracy and overall user satisfaction (quality of predictions); decrease in trustworthiness/reliability in recommendations; good or niche products might be invisible to customers; a suitable product initially poorly rated or not rated eventually getting removed from the list of recommendations (long-tail)	*(Aghili et al., 2011; Alamdari et al., 2020; Cai & Zhu, 2019; Chopra & Dixit, 2021, 2023; Chung et al., 2013; He et al., 2010; Hu et al., 2017; Huang et al., 2021; Kumar et al., 2015; Moradi & Hamidi, 2023; Singh et al., 2022; Wei & Shen, 2016; Xu et al., 2022; Yang et al., 2018; Yang & Cai, 2017; Zhang & Sheng-hua, 2007)*
	Dishonest ratings by non-malicious users	Dishonest ratings prompting misleading recommendations	*(Cai & Zhu, 2019)*
	Obtaining, tracking, storing, using, or divulging sensitive customer	Violation of individual privacy; users providing false information or not providing	*(Alamdari et al., 2020; Chen, 2022; Erkin et al., 2012; Frey et al., 2016; Hsieh, 2011;*

Category	Risk-generating events	Outcomes	Source/s
	information in an unauthorized or undesired manner	information resulting in false predictions; certain new customers moving away from e-commerce sites; users' hesitance to provide their credible preference; influence on purchase intentions, loyalty, and relationship with the brand	*Jeyamohan et al., 2019; Kashani & Hamidzadeh, 2020; Li et al., 2021; Lu & Shen, 2015; Mallik & Sahoo, 2020; Mican et al., 2020; Polat & Du, 2005; Ram Mohan Rao et al., 2018; Ran et al., 2022; Rohden & Zeferino, 2022; Vučetić & Hudec, 2018; Yan & Tang, 2011)*
	Re-using product reviews (review plagiarism) for unwarranted purposes		*(David & Pinch, 2006)*
Customer biases/actions	Customers complying with the choices of other customers (conformity/social influence bias)	Influence on user's purchase behaviour; negative impact on the quality of the recommendations provided to future customers	*(Ahmed et al., 2022; Gopalachari, 2018; Z. Wang et al., 2022)*
	Customers providing biased reviews on products are influenced by the order sequence in which existing online reviews are captured by a new customer (sequential bias)	Leading to inaccuracies in recommendations that use online customer reviews as explicit input information to generate recommendations	*(Eryarsoy & Piramuthu, 2014)*
	Customers' decision biases (irregularities in human decision making) e.g., the tendency to make decisions under certain emotional state and interests	Affecting accuracy of the recommendations	*(Ahmed et al., 2022; Gopalachari, 2018)*
	Customers contributing to data leakages	Increased privacy risks to customers	*(Ram Mohan Rao et al., 2018; Yan & Tang, 2011)*
	Customers' tendency to favour a product simply because it is ranked high (position bias) or neighbouring/related items influencing click-through rate of a target item (neighbouring bias)		*(Gu et al., 2020)*
	Customers' lack of awareness of how algorithms make product recommendations	Tendency to make inferior product choices	*(Chen, 2022)*

Category	Risk-generating events	Outcomes	Source/s
Incompetent systems	Incompetent recommender systems with functional issues (i.e., non-consideration of complex user requirements, information overload etc.)	Customers facing challenges in validating the recommendations; customers declining recommendations; customers switching to other stores	*(Kim et al., 2017; Vučetić & Hudec, 2018)*
	RS not capturing changing user preferences for products over time (user and item bias)	RS failing to capture changing customer preferences	*(Dou et al., 2021)*

Table A2: Risk-generating events, outcomes, and sources

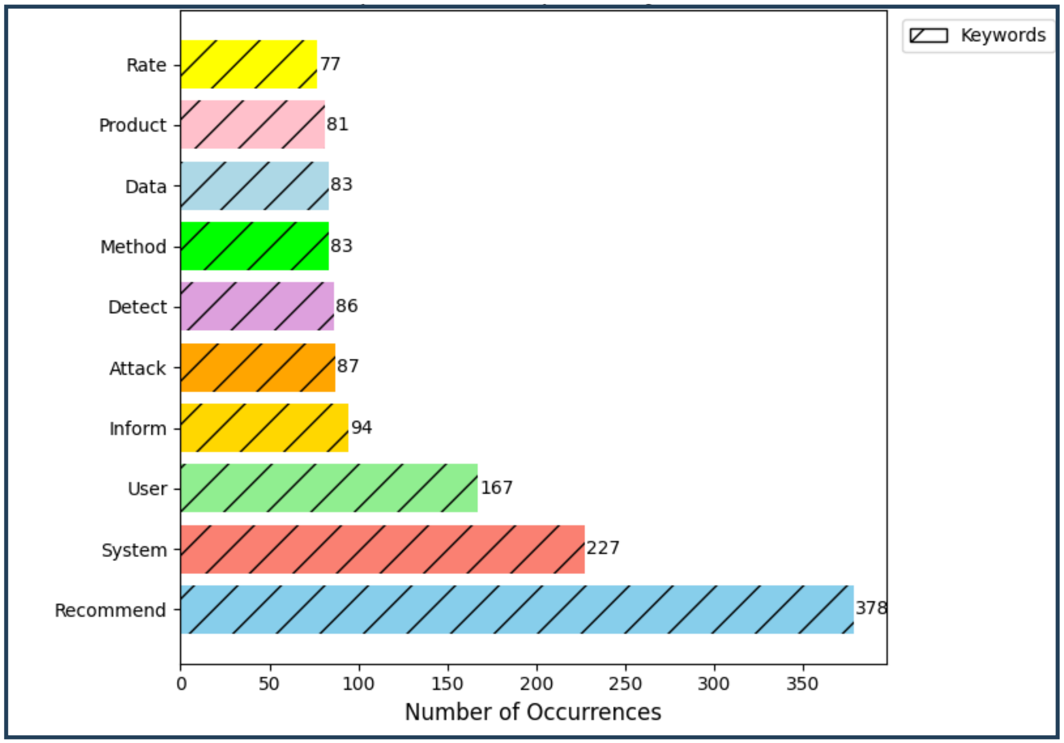

Figure A1: Top 10 most frequent keywords

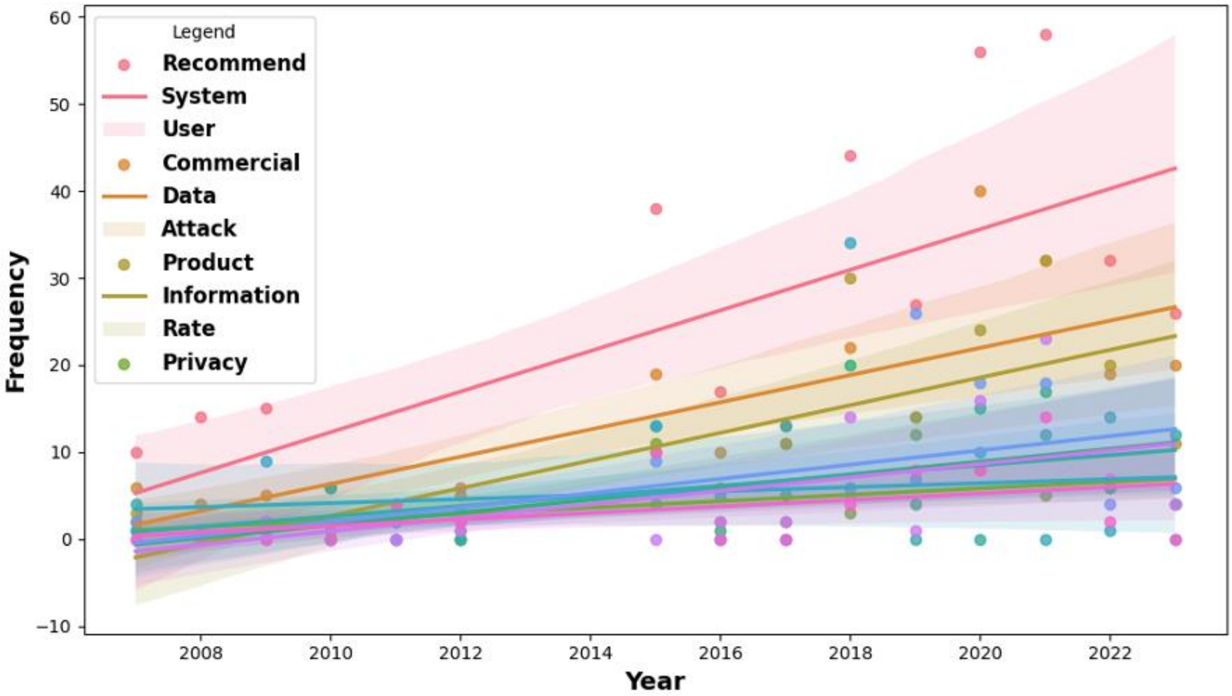

Figure A2: Keywords over years

Risk-generating events
Recommending popular products (popularity bias), less frequently purchased products, and/or ignoring unpopular/new/obscure products (long tail products)
Presenting selective/incomplete information or hiding product information
Promoting profitable products/un-profitable products
Use of biased/unbalanced user data to provide biased product recommendations to first time/lesser-known customers
Generating biased system ratings which influence subsequent customer preference ratings (anchoring effect)
Lacking the surprise element (i.e., serendipity) and/or diversity in recommendations
Presenting visually biased product recommendations and/or using biased marketing cues to promote products
Biased policies on exposing search results to customers (exposure bias)
Shilling/ Profile injection attacks (push and/or nuke attacks) by malicious users
Dishonest ratings by non-malicious users
Obtaining, tracking, storing, using, or divulging sensitive customer information in an unauthorized or undesired manner
Re-using product reviews (review plagiarism) for unwarranted purposes
Customers complying with the choices of other customers (conformity/social influence bias)
Customers providing biased reviews on products are influenced by the order sequence in which existing online reviews are displayed to a new customer (sequential bias)
Customers' decision biases (irregularities in human decision making) e.g., the tendency to make decisions under the influence of certain emotional states and/or interests
Customers contributing to data leakages
Customers' tendency to favor a product simply because it is ranked high (position bias) or neighboring/related items influencing click-through rate of a target item (neighboring bias)
Customers' lack of awareness of how algorithms make product recommendations
Incompetent recommender systems with functional issues (i.e., non-consideration of complex user requirements, information overload, etc.)
RS not capturing changing user preferences for products over time (user and item bias)

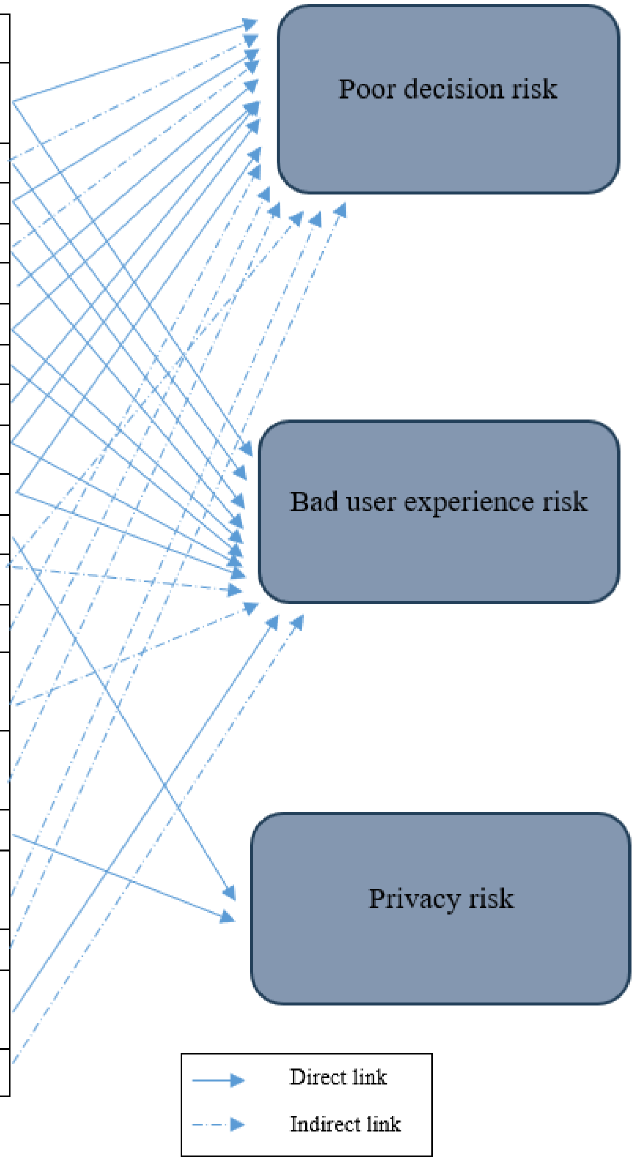

Table A3: Links between risk-generating events and risks

Copyright

doi: https://doi.org/10.3127/ajis.v28.4869