3-20-2024

Unraveling Biases and Customer Heterogeneity in E-commerce Recommendation Systems

Sachin Sharma
University of Missouri-St. Louis, ss2tk@umsystem.edu

Unraveling Biases and Customer Heterogeneity in E-commerce Recommendation Systems

Sachin Sharma

M.B.A., General Management, Emory University – Georgia, 2018
B.Tech. Mechanical Engineering, Visvesvaraya Technological University– Belagavi, 2002

A Dissertation Submitted to The Graduate School at the University of Missouri-St. Louis in partial fulfillment of the requirements for the degree
Doctor of Business Administration with an emphasis in Information Systems

May 2024

Advisory Committee

Vivek K. Singh, Ph.D.
(Chair)

Kailash Joshi, Ph.D.

Seemantini Pathak, Ph.D.

Abstract

This research explores the biases present in AI algorithms within e-commerce recommendation systems, focusing on how these biases prioritize popular, sponsored, and private-label products over actual customer preferences. We extend the responsible AI discourse by critically examining these biases and their implications for fairness in e-commerce. To strengthen the current understanding of AI fairness in the fields of information systems and computer science, we aim to challenge the assumption that AI fairness is objective and the same for everyone. We examine how individual differences, such as equity sensitivity and exchange ideology, contribute to users' varied perceptions of AI fairness. Through a factorial design survey, we find that customers perceive popularity bias as less unfair than sponsored or private-label biases, indicating a possible preference for conformity or 'herd behavior.' Further, our findings support the influence of exchange ideology, as individuals with higher levels of this trait tend to view recommendation systems as more unfair. However, we did not find similar empirical support for equity sensitivity trait. Finally, we find that perceived fairness negatively influences the distrust towards the recommendation systems. Our findings emphasize that addressing customer fairness perceptions is vital for mitigating distrust and enhancing the effectiveness of these systems. We conclude by discussing the theoretical contributions to the literature on AI and organizational justice and practical recommendations for improving the fairness of AI recommendation systems in e-commerce.

Keywords: Recommendation systems, Artificial Intelligence, Popularity bias, Sponsored bias, Private-label bias, Distrust, Perceived fairness, Equity Sensitivity, Exchange Ideology.

Table of Contents

List of Tables

List of Figures

Acknowledgments

I express my deepest gratitude to my wife, Ritu Sharma, and my entire family for their unwavering support and love throughout this dissertation process. Their presence has been the cornerstone of my resilience and motivation. My wife, in particular, has been a pillar of strength, offering constant encouragement, understanding, and patience. Her unwavering belief in my abilities and countless sacrifices have been instrumental in my academic journey. I extend my heartfelt thanks to my parents and siblings for their steadfast support and belief in my intellectual pursuits, which have significantly fueled my academic endeavors.

My appreciation also goes to my classmates and close friends – Matthew Aplin-Houtz, Mark Sanders, Sarah Willey, Emily Lane, and Sean Leahy. As part of my cohort, their collaboration, insights, and solidarity have been invaluable in navigating the challenges of dissertation. Their backing has been crucial in enhancing our collective resilience and fostering growth during the dissertation process.

I extend my profound gratitude to my dissertation chair, Dr. Vivek Kumar Singh, for his relentless guidance, invaluable input, and remarkable patience throughout this research. My sincere thanks also go to the esteemed members of my dissertation committee, Dr. Seemantini Pathak, and Dr. Kailash Joshi, for their insightful feedback and recommendations, which have significantly elevated the quality of my work.

Finally, I express my profound appreciation to the Graduate Business Program team – Dr. Ekin Pellegrini, Francesca Ferrari, and Matthew Becker, for their indispensable support and resources.

Chapter 1. Introduction

1.1. Overview

E-commerce platforms leverage AI-powered recommendation algorithms to optimize customer experience by recommending products that they may have overlooked or offer them better deals (Tam & Ho, 2006). Companies of global repute, such as Amazon and Netflix, are effectively deploying such recommendation systems (Wedel & Kannan, 2016). Hosanagar et al. (2013) note that algorithmic product recommendations account for more than 35% of Amazon.com's sales, highlighting the significant impact of these systems on boosting online sales. According to a recent study by McKinsey Global Institute, the automation potential of sales functions stands at 40%, a figure expected to rise with technological advancements, particularly in recommendation systems (De Uster, 2018). Beyond sales augmentation, recommendation systems when employed by e-commerce platforms play a crucial role in implementing dynamic pricing strategies to maximize profitability (Pathak et al., 2010).

The COVID-19 pandemic has expedited the rise of e-commerce because of customers' need for convenience and health safety, and this trend is expected to continue in the near future (Brewster, 2022). Due to the significant change in customer preferences favoring purchasing products online in 2020, it is projected that e-commerce sales will continue to rise at a rate of more than ten percent for the next few years (Lebow, 2021). Projections suggest that worldwide e-commerce sales will continue to rise, reaching $7.38 trillion by 2025. This would amount to around $23,000 per person annually in the US and account for 24.5% of the total retail sales.

The current antitrust lawsuit against Amazon alleges that the e-commerce giant has engaged in unfair methods and practices, such as manipulating product recommendation algorithms, purportedly to enhance its profitability and revenue stream (The New York Times, 2023; Politico, 2023; The Verge, 2023; Federal Trade Commission, 2023). This antitrust lawsuit alleges that earlier, the Amazon e-commerce platform provided product recommendations based on customer search queries and preferences (also known as organic or neutral recommendations); however, recent developments indicate that the platform is now suggesting product that may not match customer preferences, are expensive sponsored products, and pushes organic search results below such products[1]. Beyond e-commerce platform favoring sponsored products, the lawsuit also claims that the company promotes its private-label products (products offered under its own brand name), creating an uneven playing field for third-party products competing against its own. The overall claim is that these recommendation biases in form of promoting private-label and sponsored products harm customers' interests. However, there is a dearth of research to determine how customers perceive these unfair strategies used by e-commerce companies in their recommendation algorithms.

In addition to the biases discussed above, another significant issue faced by customers using e-commerce platforms is the apparent prevalence of popularity bias on such platforms. This bias occurs when products that are popular, such as best-sellers, are recommended, which leads to overshadowing an extensive assortment of less popular

[1] FTC antitrust lawsuit against Amazon; available online (date accessed: November 6, 2023) https://www.ftc.gov/system/files/ftc_gov/pdf/1910129AmazoneCommerceComplaintPublic.pdf

items that do not receive sufficient recognition and may be of interest to the customers (Abdollahpouri et al., 2017; Klimashevskaia et al., 2023). E-commerce companies often favor popular products, and such favoritism can cause problems because less popular or long-tail products are equally important for understanding what customers really like. The popularity bias exploits customers' weakness of herd behavior which indicates that we associate popularity with quality when making decisions (Ciampaglia et al., 2018). When e-commerce algorithms learn about customers' preferences, they should prioritize products based on customer preferences rather than focusing on popular product recommendations (Abdollahpouri et al., 2019; Nguyen et al., 2014; Resnick et al., 2013). On an e-commerce platform affected by popularity bias, lesser-known organic products that meet customer preference are pushed below popular products. Nevertheless, there is a lack of research examining how customers perceive the popularity bias.

Customers may perceive e-commerce recommendation systems as unfair when recommendation algorithms prioritize popular, sponsored, or private-label products, leading to a biased shopping experience. The perception of fairness plays an essential role in how individuals make decisions (Fehr & Schmidt, 1999; Shin, 2021; Sharma et al., 2023). This highlights that understanding fairness perception is critical in e-commerce systems, as it potentially impacts users' distrust towards such systems. In the realm of e-commerce, fairness is based on the principle that each customer should be treated equally and without any bias. This is crucial for establishing trust and sustaining a fair connection between e-commerce platforms and their customers (Shin, 2021). The customers' perception of fairness is of utmost importance as it directly impacts the adoption of new systems and their distrust of such systems (Shin, 2021). The emphasis on users' perceived fairness highlights the need to evaluate system fairness based on their subjective opinion of fairness rather than solely relying on quantifiable outcomes (Hinz et al., 2011). Therefore, in this study, we investigate how individuals perceive fairness of different recommendation systems biases.

Information systems (IS) and computer science (CS) literature assumes that algorithmic fairness is an objective concept and is the same for everyone; however, organizational justice literature has shown that individuals perceive fairness differently (Mehrabi et al., 2021; Scot & Colquitt, 2007). The examination of individual variations in sensitivity to fairness in organizational behavior has garnered considerable attention, particularly in comprehending how individuals perceive fairness and injustice within organizations (Bourdage et al., 2018; Davlembayeva et al., 2021). Equity sensitivity, a unidimensional personality trait, elucidates the intricate manner in which individuals respond to instances of organizational injustice (Bourdage et al., 2018). Prior research on AI fairness has commonly taken a uniform perspective on system fairness, assuming that all users see a system as either fair or unfair in the same way. These studies have primarily examined how users perceive the fairness of recommendation systems (Shin 2020, 2021). However, there is still a gap in our understanding that necessitates a more thorough investigation, both in theory and through empirical research, of how equity sensitivity influences the fairness of AI-driven recommendation systems.

According to Scott and Colquitt (2007), equity sensitivity is a continuum that describes traits of individuals, from being kind and generous to feeling deserving and entitled. Huseman et al. (1987) elaborate on how individuals with a benevolent nature are inclined to tolerate unfair events when they get lesser rewards in comparison to others. On the contrary, entitled individuals seek rewards, surpassing those who put in the same amount of effort. Equity-sensitive individuals who value fairness strive to earn rewards that are proportionate to their contributions. We propose that the perception of fairness in e-commerce recommendations depends on how one fits on the continuum of equity sensitivity. Specifically, a benevolent customer may view a recommendation system as fairer compared to an entitled customer. Due to the lack of clarity on this intricate link between equity sensitivity and perceived fairness in the current body of literature, we are driven to conduct research and address this gap within the realm of e-commerce recommendation systems.

Along the lines of equity sensitivity, exchange ideology measures individuals' preferences in an exchange transaction. While customers typically expect a fair exchange, some may favor being generously rewarded, while others may be willing to accept a less-than-expected return. Consideration of exchange ideology may also help understand the variations in customer fairness perceptions in online transactions. The concept of exchange ideology evaluates an individual's level of sensitivity towards fairness in exchange scenarios (Scott & Colquitt, 2007). Nevertheless, there is a paucity of research examining the impact of exchange ideology on perceived fairness in the context of recommendation systems. We address this important literature gap.

Previous studies suggest that trust and distrust constructs are not simply opposites; instead, they can coexist, and both significantly affect how people interact with each other and within organizations (Benamati et al., 2006; Connelly et al., 2012;

Dimoka, 2010; Komiak & Benbasat, 2008; Ou & Sia, 2010). Distrust is a widespread issue that arises from perceived breaches of trust. Its implications affect both personal behavior and broader societal interactions (Wang et al., 2018).

In the context of e-commerce, distrust is just as important as trust, and it plays a unique and significant role in the e-commerce environment. The effect of distrust extends beyond simple low trust levels, significantly influencing customer behavior and the dynamics of e-commerce transactions (Moody et al., 2014; Wang et al., 2018; Lee et al., 2015). The significance of distrust in the e-commerce marketplace is highlighted by its direct impact on business outcomes, where skepticism towards digital systems, like recommendation engines, can lead to reduced customer engagement. This, in turn, can harm a brand's reputation and potentially lead to legal issues (Cho, 2006; Shin, 2021). While the concept of distrust has been introduced in the prior literature recently, its significance within the realm of AI-based recommendation systems remains largely unexplored (Wang et al., 2018).

Although trust has been studied in the context of recommendation systems, distrust is a more suitable construct in the context of biased recommendation systems. Individuals who perceive a recommendation system as unfair will probably have higher distrust towards such a system. Recognizing this distinction is crucial for understanding customer behavior, especially in situations where distrust, seen as an anticipation of unfair actions, influences their interactions with e-commerce platforms (Lewicki et al., 1998; McKnight & Choudhury, 2006; Sitkin & Roth, 1993; Wang et al., 2018).

1.2. Research Questions

This research efforts aim to study how distrust towards e-commerce platforms is influenced by perceptions of fairness of biased recommendations, as well as the degree to which individual characteristics such as exchange ideology and equity sensitivity affect these views. Given the growing dependence on algorithmic decision-making in e-commerce settings and the possible effects it may have on customer behavior, this investigation is essential. Based on the preceding discussion, the following research questions arise:

RQ1: *How do different biases in e-commerce recommendation systems impact perceived fairness?*

RQ2: *How does customers' perceived fairness of recommendation systems impact their distrust of e-commerce platforms?*

RQ3: *How do customers' equity sensitivity and exchange ideology impact their perceived fairness of recommendation systems employed by e-commerce platforms?*

1.3. **Contributions**

This study finds that customers perceive popularity bias in recommendation systems relatively less unfair than the other two biases, i.e., sponsored and private-label bias. It found no support for the hypothesis that individuals with higher equity sensitivity (on the entitled side) perceive recommendation systems as less fair than individuals with lower equity sensitivity (on the benevolent side). However, individuals with a strong exchange ideology find recommendation systems less fair than individuals with a weak exchange ideology. Finally, the study finds that the perceived fairness of individuals towards recommendation systems is negatively related to their distrust of such systems.

This study contributes to the field of AI ethics and equity by highlighting how the personality trait - exchange ideology affect perceptions of fairness in recommendation systems (Scott & Colquitt, 2011). Additionally, it uncovers a connection between herd behavior and the perception of algorithmic biases, offering insights into how individuals identify and react to various types of biases (Sun, 2013; Feng, 2022). Further contributing to the literature on trust in information systems, our research underscores the importance of considering distrust as an important outcome construct when examining the impacts of algorithmic biases (Shin, 2021). Further, by segmenting customers based on how they perceive fairness, and including factors like exchange ideology, e-commerce platforms can develop tailored strategies for different customer interactions. This approach may reduce distrust towards these platforms, ensuring a more personalized and satisfactory customer experience.

Chapter 2. Literature Review

This literature review presents a comprehensive analysis of recommendation fairness and biases in the fields of Information Systems (IS), Computer Science (CS), and business, highlighting the research gaps in extant literature. Subsequently, we provided an overview of the existing literature on distrust in recommendation systems, along with studies on equity sensitivity and exchange ideology. Figure 1 highlights the multidisciplinary nature of our research by showing the primary focus of our work, which is situated at the intersection of three important streams of literature: recommendation systems, responsible AI and e-commerce. Recommendation systems are a core component of e-commerce platforms, using algorithms to suggest products to customers based on various factors like past purchases, browsing history, and user preferences. Responsible AI, on the other hand, encompasses ethical considerations and fairness in the development and deployment of AI technologies, including recommendation systems. By positioning e-commerce within the intersection of these two areas, we are not only focusing on how e-commerce platforms leverage algorithms to influence customer behavior but also on the broader implications of these systems related to fairness, bias, and ethical responsibility (Vassilakopoulou et al., 2022).

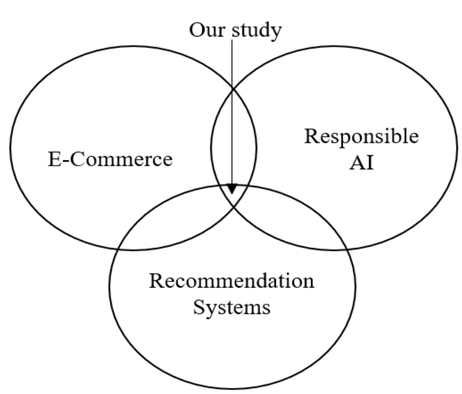


Figure 1 Literature gap

2.1. Recommendations Systems in IS Research

Prior research in the field of Information Systems (IS) primarily aimed to enhance the functionality, accuracy, and usefulness of recommendation systems (Alamdari et al., 2020; Fayyaz et al., 2020). Over time, recommendation systems in IS have evolved from simple content-based models to complex systems that employ advanced algorithms to deliver sophisticated recommendations. The application of artificial intelligence (AI) in recommendation systems has significantly improved their efficiency, resulting in product recommendations that are better aligned with customer preferences (Dash et al., 2021).

While the existing body of research on recommendation systems has greatly enriched our understanding, a significant gap remains in exploring recommendation system biases in the context of e-commerce (Zang and Jin, 2021; Fayyaz et al., 2020; Dast et al., 2021; Shin, 2021). Extending the previous studies on AI-powered recommendation systems (Xiao and Benbasat, 2015; Peng et al., 2023; Adomavicius et al., 2018; Wang & Wang 2019; Wang et al., 2018; Sharma et al., 2023), the goal of our study is to investigate how algorithmic recommendation biases impact individuals' perception of fairness based on their personality traits.

2.2. Perceived Fairness

The role of perceived fairness is crucial as it significantly influences user trust, the perceived utility of algorithms, and overall satisfaction with the system, as evidenced by studies like those by Shin & Park (2019) and Shin et al. (2020). Shin et al. (2020) further explored how individuals' perceptions of fairness affect their experiences and attitudes toward the algorithm. Foundational research by Dwork et al. (2012) and Hajian et al. (2016) has highlighted key influencing factors such as transparency, accountability, and the importance of providing explanations for algorithmic decisions. These elements were also emphasized by Diakopoulos (2016) and Binns (2018) as critical for enhancing user understanding and trust in algorithmic systems.

While prior studies have focused on developing behavioral models to discern the antecedents and consequences of perceived fairness, a critical dimension remains largely unexplored: the impact of specific types of biases in recommendation systems—such as popularity bias, sponsored bias, and private-label bias—on the perceived fairness among e-commerce customers. Furthermore, there is a need to investigate how individual differences, such as equity sensitivity and exchange ideology, modulate perceptions of fairness in the context of e-commerce recommendations. These individual-level factors could significantly influence how users interpret and respond to the fairness of algorithmically generated recommendations.

2.3. Recommendation Fairness and Biases

The inclusion of AI introduces potential challenges such as lack of transparency, and concerns regarding the diversity and fairness of the recommendations made (Li et al., 2021; Shin, 2021). When examining the ethical dilemmas associated with AI-powered recommendation systems, key concerns such as bias and fairness stand out (Dash et al., 2021; Shin, 2021; Wang et al., 2018; Abdollahpouri et al., 2019). To promote fairness in these intelligent systems, it is essential to thoughtfully design algorithms and scrutinize data sources, thereby mitigating biases that may unfairly favor certain user groups or products (Li et al., 2021).

The concept of fairness has recently gained significant importance in the field of artificial intelligence, evidenced by a growing body of literature (Shin, 2021; Dash et al., 2021; Wang et al., 2018, Abdollahpouri et al., 2017; Klimashevskaia et al., 2023; Sharma et al., 2023). Recent studies on algorithmic bias have adopted two fundamental frameworks: individual fairness and group fairness (Binns, 2020; Mukherjee et al., 2020; Fleisher, 2021). Individual fairness requires treating similar individuals in a comparable way. However, precisely defining this concept is challenging due to the absence of agreement on metrics for measuring individual similarity. In artificial intelligence, fairness is the belief that individuals should be treated similarly, yet determining and quantifying individual similarity can be difficult because there isn't consensus on specific requirements.

In computer science (CS), recommendation fairness is generally viewed as an objective concept (Mehrabi et al., 2021). However, studies in organizational justice indicate that perceptions of fairness vary significantly among individuals, challenging this objective view (Scott & Colquitt, 2007). To better understand these variations, we leveraged the constructs such as equity sensitivity and exchange ideology from the literature on organizational justice, which help in understanding the disparities in perceived fairness (Scott & Colquitt, 2007). The marketing literature on equity sensitivity and exchange ideology provides valuable insights into customer behavior and organizational dynamics. Wheeler (2002) found a direct correlation between equity sensitivity and cultural values such as collectivism, femininity, and power distance for a diverse sample within the United States. Scott and Colquitt (2007) discovered that exchange ideology significantly influences the link between justice and outcomes, unlike equity sensitivity, highlighting the complex role of individual traits in organizational contexts. King and Miles (1994) also noted a correlation between equity sensitivity and various personality attributes, including exchange ideology, suggesting a nuanced interplay between these concepts.

Our literature review highlights the significance of responsible AI, which aligns with the broader implications of algorithmic decision-making in e-commerce platforms. The study focuses on the intersection of recommendation systems and responsible AI. Its goal is to contribute to the discussion on distrust and the ethical use of AI technologies in improving customer experience. It also aims to ensure fairness and diversity in recommendations.

The topic of fairness in intelligent decision-making systems, especially in recommendation systems, has gained substantial attention (Ge et al., 2021; Wang et al., 2023; Li et al., 2021). This growing attention reflects the multifaceted nature of fairness, a concept that spans various disciplines and is context dependent. Fairness, also known as organizational justice, has been prominent in organizational behavior and management research. A seminal work by Adams (1965) laid the groundwork for critical concepts like equity theory and procedural justice theory. This research delved into the mechanics of exchange processes in human interactions, highlighting their significance in driving motivations and behaviors. Adams' theory emphasizes the critical role of viewing social exchanges from the perspective of relative deprivation and gratification. These factors are essential in forming perceptions of fairness and unfairness.

Although Adams' work offers foundational insights, it mainly focuses on interpersonal and organizational settings. Extending this work to the realm of recommendation systems and algorithmic fairness brings about distinct challenges and considerations. Fairness must be reconceptualized in the realm of recommendation systems to accommodate the complexities of algorithmic decision-making, where data-driven algorithms replace human-like exchange processes. This shift necessitates a reevaluation of traditional fairness theories. In AI-based systems, fairness is often associated with mitigating biases that can arise due to algorithmic processing. Our study focuses on three specific types of biases: popularity bias, sponsored bias, and private-label bias. These biases represent distinct challenges in ensuring fairness.

Dash et al. (2021) studied biases in Amazon's recommendation systems, highlighting an over-representation of Amazon's private-label and sponsored product recommendations. In our study, we aim to broaden the investigation of biases within e-commerce systems, extending the research by Dash et al. (2021). Their study found an over-presence of Amazon's proprietary brands and sponsored product recommendations. Our study extends this research and seeks to examine how these biases impact perceived fairness and distrust towards such platforms. We also emphasize the need for further comprehensive investigations into biases across different e-commerce platforms. We present a clear distinction between biases, such as popularity bias, sponsored bias, and private-label biases, and examine how these biases affect the fairness and distrust of e-commerce recommendation algorithms.

While Shin's (2021) research demonstrates a relationship between perceived fairness and trust, it does not consider the potential impact of individual traits, such as exchange ideology and equity sensitivity, on this relationship. We extend these findings and investigate the crucial role that perceived fairness plays in either fostering or diminishing customer distrust.

2.3.1. Popularity Bias

Popularity bias presents a significant challenge in recommendation systems, wherein a recommendation system disproportionately favors more popular items such as best-sellers products and consequently neglects users' preference for lesser-known, niche offerings (Abdollahpouri et al., 2019; Wei et al., 2021; and Klimashevskaia et al., 2023). Recommendation algorithms on these platforms significantly contribute to ranking inconsistencies by favoring already popular products, which can disadvantage newer or lesser-known items (Cheng et al., 2011; Harvey, 2003; Ransom, 2010; Yang & Ghose, 2010; Zhang et al., 2021). Furthermore, when recommendation systems favor certain products, it can result in unfair advantages, pushing down organic products for the customers (Wang & Wang, 2019). Our study investigates how popularity bias impacts customer views of fairness, comparing it to other biases to shed light on the broader consequences of algorithmic biases in e-commerce contexts.

2.3.2. Sponsored Bias

As e-commerce platforms continue to evolve, sponsored product recommendations have become an integral part of the customer experience. Prior studies have explored the growing influence of such products on e-commerce recommendation systems (Dash et al., 2021; Wang et al., 2018; Xiao and Benbasat, 2015; Wang et al., 2018; Ricci et al., 2011; PricewaterhouseCoopers, 2017). Such recommendation systems often prioritize sponsored products that may not match customer interests (Animesh et al., 2007; Guijarro et al., 2015). This shift towards pay-for-placement strategies by e-commerce platforms, where sponsors compete for prominence in recommendation lists, raises concerns among customers (Katona & Sarvary, 2010).

Extant literature in the field of algorithmic fairness has typically concentrated on eliminating bias based on demographic factors such as race, gender, or age (Dwork et al., 2012). However, the concept of sponsored product bias introduces a different dimension, where biases are introduced not by inherent algorithmic flaws but by commercial influences (Lee et al., 2019). Our research focuses on the bias within recommendation systems that preferentially boost sponsored products, disregarding whether these products are the best match for the customer's stated preferences. While sponsored products may not inherently be of lower quality, their prioritization may not be aligned with customer preferences (Krishnasamy et al., 2015). The significance of this bias highlights the need for managers to be aware of its potential effects on customer perceived fairness of the recommendation platforms (Kramer et al., 2013; Guijarro et al., 2015).

E-commerce platforms like Amazon display sponsored products, even though these sponsored products do not fulfill the specific user criteria (Wang and Wang, 2018; Wang et al., 2019). These studies also highlight the typical practice of websites like Expedia.com ranks sponsored items prominently at the top of search and recommendation listing, which is observed across different platforms. Although this stream of research has explored sponsored products, they have not compared its effect with other biases.

2.3.3. Private-Label Bias

Platform-owned private-label products often receive preferential treatment due to the financial incentives of the platforms (Dash et al., 2021). This leads to the bias toward private-label products when algorithms disproportionately promote these products compared to the products that would potentially meet customers' preferences (Dash et al., 2021). An example is when Amazon allegedly limits its "Tier 1 Competitors" from advertising on its platform, specifically when users seek its private-label devices, such as Fire TV or Echo Show (Mattioli et al., 2020).

Considering these concerns, regulatory bodies are increasingly considering interventions. For instance, the Indian government has enforced legislation to ensure fair treatment of all sellers on digital platforms (Press Information Bureau, 2018), and the European Commission has launched an antitrust investigation into Amazon's practices with independent vendors (White & Bodoni, 2020). U.S. regulators have raised similar concerns, indicating global scrutiny of online marketplace practices.

While previous studies have focused primarily on specific platforms (Dash et al., 2021; Abdollahpouri et al., 2019; Shin, 2021), our goal in this research is to gain a thorough understanding of how these biases affect users' perceptions of fairness and subsequently their lack of trust in the platforms.

2.4. Distrust

Trust and distrust have been extensively explored in academic research as critical constructs, with their interplay profoundly affecting user perceptions and behaviors. Building on the foundational work by Barber (1983) and Rousseau et al. (1998), which posits distrust as the conceptual opposite of trust, subsequent studies have delved deeper into these dynamics. Mayer et al. (1995) noted that a decrease in trust typically signals the emergence of distrust. This relationship was further expanded by Lewicki and Bunker (1996), who underscored the influence of communication, exchange, and perceived benevolence on the development of trust and distrust in interpersonal contexts. Dirks and Ferrin (2001) extended this understanding to organizational settings, emphasizing the critical role of trust and distrust in shaping employee relationships and organizational outcomes.

In the context of algorithm-based recommendation systems, trust is defined as the confidence users place in the system's ability to provide reliable information (Wang & Wang, 2019). Conversely, distrust arises from goal and value inconsistencies between the user (trustor) and the system (trustee) (Connelly et al., 2012; Hardin, 2004; Lewicki et al., 1998; Wang et al., 2019). The early research by Luhmann (1979) and Kahneman & Tversky (1979) laid the foundational understanding of trust and distrust as *distinct constructs* with their own positive and negative connotations, respectively. This idea was further solidified by Cacioppo & Berntson (1994) and Cacioppo et al. (1997), who demonstrated through their work that positive and negative evaluations are separate processes, each characterized by its own precursors and consequences, thus reinforcing the conceptual division between trust and distrust.

In Information Systems (IS), distrust has been identified as a pivotal element impacting user behavior and decision-making. McKnight et al. (2002) addressed distrust in e-commerce, highlighting security and privacy concerns as critical determinants of customer trust and distrust in online transactions. Despite extensive research in this area, gaps still need to be filled in our understanding of the complexities of distrust, its development, and strategies for mitigation.

Recent studies, such as Wang et al. (2018), have investigated the impact of sponsorship bias in recommendation systems—with and without disclosure—on user trust and distrust. They explored how psychological contract violation mediates this relationship and contributed to understanding the differential patterns in trust improvement and distrust mitigation in recommendation systems. The persistence of distrust, especially once established, present challenges in its elimination (Connelly et al., 2012; Dirks & Skarlicki, 2004). Various factors, including perceived biases, lack of transparency, privacy concerns, and personalization flaws, shape distrust toward e-commerce recommendation systems. Addressing these concerns reduces customers' distrust and ensures successful e-commerce transactions.

Gorgoglione et al. (2019) noted that perceived biases in recommendation algorithms often lead to user distrust, emphasizing the importance of understanding user perceptions and responses to these biases. Inaccuracies in personalized recommendations are another significant source of customer distrust, highlighting the need for improving algorithmic precision to restore and maintain user confidence. Existing literature extensively explores trust in various contexts, yet a significant gap remains in understanding how online shoppers perceive and respond to algorithmic biases in recommendation systems and how these biases influence their distrust.

2.5. Equity Sensitivity

Equity sensitivity is a key concept in Adams's (1965) equity theory and has been extensively studied in organizational behavior. This theory, which finds its foundation in social comparison and exchange theories, posits that individuals assess fairness based on the ratio of their inputs (such as effort, time, and energy) to outputs (like rewards) in comparison to others (Adams, 1963, 1965). While there has been an extensive exploration of equity sensitivity within organizational behavior contexts (e.g., Scott & Colquitt, 2007; Bourdage et al., 2018; Sauley & Bedeian, 2000; O'Neill & Mone, 1998;

Kickul & Lester, 2011), its role in information systems, especially AI-driven recommendation systems, is underexplored.

The construct of equity sensitivity (ES) has recently emerged as a significant factor in retail and marketing literature, shedding light on its impact on customer behavior and attitudes, especially toward sales promotions (Fam et al., 2021). Benevolent individuals, characterized by their tolerance for under-reward situations and placing more importance on the work (input) than on pay (rewards), exhibit more positive reactions and satisfaction in response to sales promotions compared to those with entitled traits, who prefer receiving more than they contribute and place greater importance on pay (King et al., 1993; Kickul & Lester, 2001). Research by Fam et al. (2021) further demonstrates how equity sensitivity influences customer attitudes in retail environments. This finding underscores the importance of understanding different customer segments' nuanced preferences and reactions in retail settings (Fam et al., 2021). However, since this study is predominantly focused on walk-in customers in Hong Kong using a shopping mall-intercept method, it presents a limitation regarding the broader applicability of its conclusions, including digital platforms (Fam et al., 2021).

Shin (2020) explored how explainability and causability in AI impact user trust and attitudes, emphasizing the importance of AI systems being interpretable and understandable from a human factors perspective. Shin (2021) conducted a different study to investigate how users perceive algorithmic decisions made by personalized AI systems. The study focused on how users' perceptions and trust are shaped by fairness, accountability, transparency, and explainability. While previous research has concentrated on evaluating the perceived fairness of recommendation systems (Shin, 2020; 2021), empirical investigations into how equity sensitivity impacts the fairness of AI-based recommendation systems have yet to be done.

Our study addresses the above gap by exploring the concept of equity sensitivity within the realm of AI-based recommendation systems on e-commerce platforms. This research is crucial today when digital interactions are increasingly personalized and influential in shaping customer decisions. By shifting the focus from traditional retail environments to e-commerce, we seek to understand how customers react to AI-driven recommendations and whether the findings of equity sensitivity observed in physical retail settings translate to online environments. Our study will provide insights into the interplay between AI-based personalization and customer equity sensitivity traits, offering a fresh perspective on customer behavior in the digital age. By bridging organizational behavior theories with information systems practice, this study contributes to a more nuanced comprehension of user interactions with AI-based systems, particularly regarding fairness perceptions.

2.6. Exchange Ideology

Exchange ideology, a concept rooted in social exchange theory, has been a focal point in organizational behavior research, particularly in exploring individuals' attitudes and beliefs within social exchange relationships (Cropanzano & Mitchell, 2005). Originating from the seminal works of Homans (1958) and Blau (1964), social exchange theory suggests that expectations of reciprocity and mutual benefit drive social interactions. Eisenberger et al. (1986) expanded on this by positing that individuals with a strong exchange ideology are firmly committed to the norm of reciprocity, believing in reciprocating assistance to those who have aided them.

The significance of exchange ideology extends to perceptions of organizational fairness. Scott & Colquitt (2007) suggested that individuals with a strong exchange ideology may be more impacted by fair treatment than those with a weaker orientation towards exchange. Cropanzano and Mitchell (2005) further studied the role of exchange ideology in shaping employees' attitudes and behaviors in corporate environments. Their seminal work underscores the influence of social exchange principles, such as trust, reciprocity, and fairness, on workplace outcomes. While our current study of customer interactions with recommendation systems aligns somewhat with existing research, our primary objective is to investigate how the exchange ideology trait of customers influences their perceived fairness towards these systems.

Blau and Boal (1989) explored the relationship between psychological contracts, closely tied to exchange ideology and their influence on employee attitudes and behaviors. This work highlighted the dynamic nature of psychological contracts and their relevance in understanding the reciprocal interactions between employees and organizations. Additionally, Settoon and Mossholder (2002) examined the role of organizational support in shaping individuals' exchange ideologies. Their research emphasized how perceived organizational support influences exchange ideologies, subsequently impacting job performance and organizational commitment.

Despite thorough research into exchange ideology within organizational fairness and employee reactions, there's a significant gap in applying these concepts to e-commerce recommendation systems. We lack a clear understanding of how customers' exchange ideologies affect their views on the fairness of recommendations made by these systems. Filling this research gap is crucial for a comprehensive understanding of e-commerce interactions and for discerning how exchange ideology influences customer response to recommendation systems.

Chapter 3. Theory and Hypothesis Development

3.1. Psychological Contract Violation (PCV) Theory

The Psychological Contract Violation (PCV) theory, as proposed by Rousseau (1989), plays a critical role in understanding the dynamics of social exchange relationships. It centers on psychological contracts in which individuals hold beliefs about reciprocal obligations and expect benefits within these relationships. A discrepancy between the expectations set by the psychological contract and the actual outcomes constitutes a psychological contract breach or violation (Topa et al., 2022). Such breaches often precipitate a range of attitudinal and behavioral responses, including anger, distress, and feelings of betrayal (Deng et al., 2018; Wiechers et al., 2022; Wang and Wang, 2019).

Recent research has delved into the complexities of psychological contract breaches within the context of algorithmic management, contrasting these with traditional interactions involving human agents. This line of inquiry investigates how perceptions of psychological contract breaches differ when managed by algorithms versus human agents and the subsequent outcomes of these perceptions (Pavlou and Gefen, 2005; Wang and Wang, 2019). It is especially relevant in the context of recommendation systems, where there is an inherent expectation for unbiased recommendations that prioritize customer interests (Wang and Wang, 2019).

In e-commerce, psychological contracts are vital in the buyer-seller interaction, a typical example of a social exchange. The perspective of PCV provides valuable insights into customers' transactional behaviors on e-commerce platforms, where algorithms play a pivotal role in shaping and fulfilling these psychological contracts. Prior literature has identified three biases in the context of e-commerce platforms managed by recommendation systems: popularity bias, sponsored product bias, and private-label bias (Dash et al., 2021; Abdollahpouri et al., 2019; Wang et al., 2018). These biases represent deviations from the expected unbiased nature of product recommendations, constituting potential violations of the psychological contract between the e-commerce platform and its customers.

Understanding these violations is critical, as it allows for a deeper comprehension of how customers perceive and react to these biases and the broader implications for distrust in e-commerce interactions. Based on PCV arising from recommendation biases, we can propose that online shoppers' perception of such biases will lead to distrust towards the recommendation systems (Wang and Wang, 2019) and the platforms that host them. Shin (2021) argues that one of the predictors of trust is perceived fairness, which means perceived fairness precedes trust and distrust. Therefore, we can hypothesize that popularity bias, sponsored bias, and private-label bias in product recommendations will negatively influence shoppers' perceived fairness toward a recommendation system.

H1a*: A customer who encounters popularity bias in a recommendation system will perceive it as less fair than a customer who does not encounter such bias.*

H1b*: A customer who encounters sponsored bias in a recommendation system will perceive it as less fair than a customer who does not encounter such bias.*

H1c*: A customer who encounters private-label bias in a recommendation system will perceive it as less fair than a customer who does not encounter such bias.*

3.2. Theory of Herd Behavior

The concept of herd behavior, where individuals mimic the actions and choices of a crowd, offers interesting and important insights into behavioral economics and social psychology (Sun, 2013; Feng, 2022). Herd behavior highlights the inclination of humans to adhere to collective behaviors based on the belief that these acts are favorable or fair options (Celen and Kariv, 2004; Raafat et al., 2009). This behavior may influence the perceived fairness of a transaction not just through individual beliefs but also through the visible actions and sentiments of others. Further, it is crucial when analyzing social norms and collective behaviors, especially on e-commerce platforms.

Prior research indicates that peer behavior significantly influences adoption decisions. It also introduced the concept of a herding information signal, or herding cue, which informs individuals about the participation of others (Hsieh et al., 2008; Karahanna et al., 1999; Feng et al., 2022; Aplin-Houtz et al., 2023). These cues are easy to detect and process due to their simplicity, mediating the impact of individual beliefs on the adoption process (Macmillan, 2002; Aplin-Houtz et al., 2022; Leahy et al., 2023).

Further exploring the rationality behind herd behavior, Lowry et al. (2023) analyzed its role in Peer-to-Peer (P2P) lending. Contrary to the view of herding as irrational, their findings suggest it can address information asymmetry in online microloan platforms. By examining the influence of experienced lenders on novices, the study indicates that rational herding can reduce losses from borrower defaults, thus showing its positive implications.

In the context of e-commerce recommendation systems, we hypothesize that individuals' decision-making processes are susceptible to the influences exerted by the actions and choices of their peers. Our research aims to delve into the impact of popularity bias on the perception of fairness in product recommendation systems framed through the lens of herd behavior. By comparing customer experiences across popularity, sponsored, and private-label biases, we hypothesize that popularity bias in recommendation systems is perceived as less unfair than the other biases due to herd behavior. This prompts us to formulate the following hypothesis:

H1d: *A customer who encounters popularity bias in a recommendation system will perceive it as more fair than a customer who encounters sponsored or private label biases.*

3.3. Equity Theory

Equity theory, grounded in social comparison and exchange theories, provides a robust framework for analyzing how individuals perceive fairness in various contexts (Adams, 1963, 1965). In e-commerce, this study leverages equity theory to scrutinize customers' perceptions of fairness in their interactions with recommendation systems. These interactions represent a form of social exchange wherein the dynamics of equity theory are particularly pertinent.

3.3.1. Equity Sensitivity

Existing literature has examined equity sensitivity in the context of organizational behavior (Scott and Colquitt, 2007; Bourdage et al., 2018; Sauley and Bedeian, 2000; O'Neill and Mone, 1998; Kickul and Lester, 2011). O'Neill and Mone (1998) discovered that equity sensitivity interacted with self-efficacy to predict job satisfaction and intent to leave, but not organizational commitment. The study revealed that those who possessed a higher sense of entitlement showed a lower level of job satisfaction and a stronger inclination to leave their current employment, irrespective of their levels of self-efficacy. Kickul and Lester (2001) examined how equity sensitivity influences the connection between psychological contract breach and employee attitudes and behaviors. Nevertheless, there is a need for more research examining equity sensitivity in the information systems discipline to understand the variations in individual perceived fairness toward recommendation systems outcomes. It is hypothesized that a customer who is considered entitled, i.e., has a high sensitivity to equity, may consider recommendation systems to be unfair since the customer considers fairness by comparing their input-output ratio to that of other customers. Therefore, they may perceive the recommendations as biased to them than to others for the same system. On the other hand, benevolent customers who do not place a high value on equity are more inclined to view the results favorably and accept the system's suggestions even when their own gain may be smaller than that of others. With that, we hypothesize that,

H2: *A customer with high equity sensitivity (entitled customer) will perceive recommendation systems as less fair than a customer with low equity sensitivity (benevolent customer).*

3.3.2. Exchange Ideology

Eisenberger et al. (1986) found that those who have a strong exchange ideology strongly believe in the norm of reciprocity, which means they feel obligated to help those who have benefited them. Individuals who strongly adhere to an exchange ideology are likely to be more affected by unfair treatment within an organization compared to those who have a weaker adherence to this ideology (Scott and Colquitt, 2007). Research studies examining how exchange ideology affects individuals' attitudes have mostly found a positive connection. For example, Witt (1992) discovered that exchange ideology changed how people felt about decision-making involvement, especially regarding satisfaction with opportunities, goals, and organizational support. Another study conducted by Witt and Broach (1993) found that exchange ideology had an impact on individuals' satisfaction with work training programs in terms of fairness.

While prior research has focused on the perceived fairness of recommendation systems (Shin 2020, 2021), as far as we know, there has been no empirical investigation of the impact exchange ideology on the fairness of AI-based recommendation systems. Exchange ideology is relevant in the shopping context because it reflects an individual's beliefs and attitudes toward the fairness of the exchange process (Scott and Colquitt, 2007). In online shopping, where transactions occur frequently, customers form perceptions about the fairness of pricing, promotions, and value received in exchange for their money. Perceived fairness is also likely influenced by an individual's sensitivity to fairness issues, identified in the literature as individuals' exchange ideology.

In e-commerce, customers with a high exchange ideology will respond to the unfairness of the recommendation system by becoming less interested in transacting on the e-commerce platform than those with a low exchange ideology (Scott and Colquitt, 2007). Additionally, as noted earlier, Scott and Colquitt (2007) presented exchange ideology as a new measure of individual sensitivity to equity issues, which may be more appropriate to study as it helps us understand the reciprocal expectations between buyers and sellers in e-commerce. Thus, in light of the above, the following hypotheses are proposed:

***H3**: A customer with a high exchange ideology will perceive recommendation systems as less fair than a customer with a low exchange ideology.*

3.4. Distrust

In the realm of e-commerce, understanding customer perceptions is crucial for the effective functioning of recommendation systems. This study hypothesizes that perceived fairness in interactions with recommendation algorithms plays a pivotal role in shaping customers' levels of trust and distrust towards these systems. Specifically, it is posited that a heightened sense of fairness experienced by online shoppers, characterized by fair and unbiased product recommendations, will be inversely correlated with their levels of distrust.

This hypothesis is grounded in the notion that when customers perceive recommendation algorithms as fair and devoid of biases such as favoritism towards sponsored products, popularity, or private-label items, their distrust towards these systems will likely decrease. This inverse relationship is indicative of the idea that fairness perceptions act as a buffer against distrust. This proposition aligns with the principles of the psychological contract violation theory, which posits that the fulfillment or breach of implicit fairness expectations in digital transactions is a critical factor influencing trust dynamics (Wang et al., 2018). In the light of the above arguments, the following hypothesis is proposed:

***H4:** Perceived fairness will have a negative effect on perceived distrust.*

Figure 2 depicts our overall research model. The model incorporates the hypotheses and the relationships identified based on the preceding theoretical analysis. Additional variables such as respondents' gender, age, education, salary, ethnicity, and e-commerce platform usage experience are also included to control their influence on the model parameters.

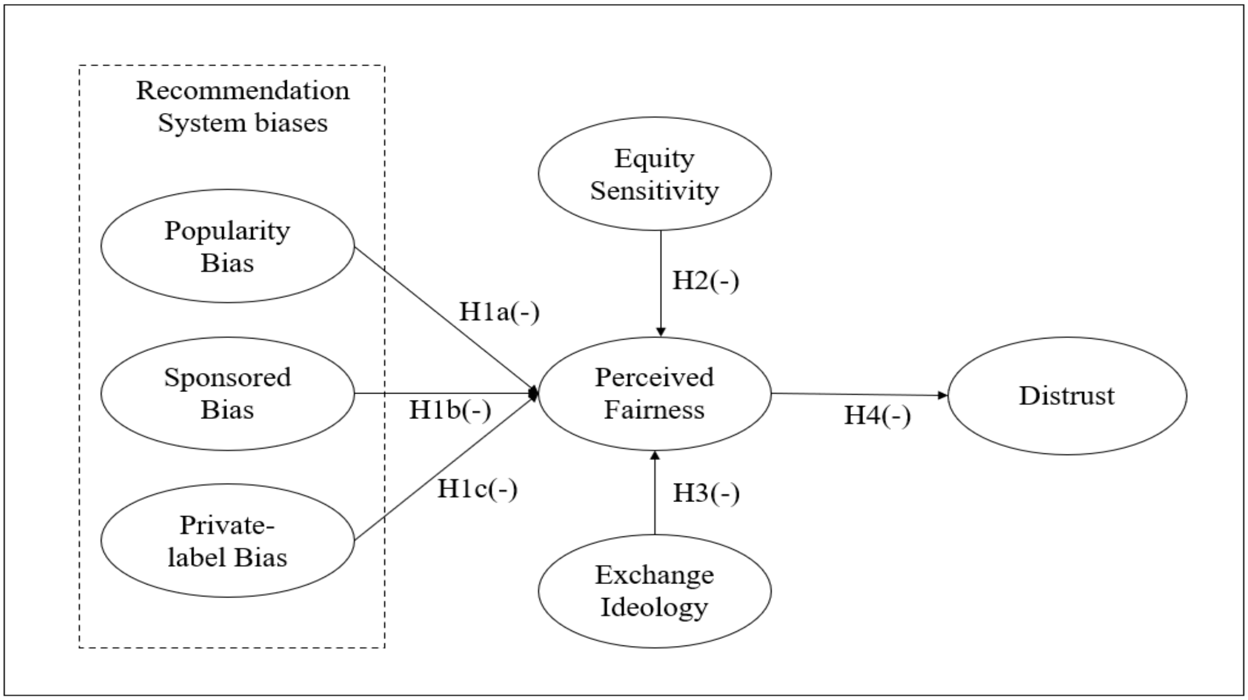


Figure 2 Research Model

Chapter 4. Research Method

To test our hypotheses, we adopted a factorial design approach for our survey. This approach is effective in designing lab experiments with multiple variables and their interactions (Jasso, 2006; Wallander, 2009; Wang and Wang, 2019; Krishnan, 2020). In our research, we adopted a between-subjects experiment design, aligning with the experimental approach commonly employed in information systems (IS) research for the development and testing of theories related to customer behavior (Mousavi et al., 2023; Adomavicius et al., 2017).

We selected the Prolific platform for participant recruitment because it strictly adheres to ethical and legal standards, which is crucial for conducting credible, high-quality research. The platform provides access to a diverse global participant pool, enhancing the generalizability and relevance of study findings (Douglas et al., 2023; Eyal et al., 2021; Palan and Schitter, 2018). Additionally, Prolific's strong data quality control procedures ensure genuine and dependable responses, reducing the likelihood of data contamination and improving the validity of the results (Smith et al., 2016). This study highlighted that Prolific is renowned for its efficacy and usability in data collection, offering researchers access to a broad and diverse pool of participants.

4.1. Experimental Flow

We adopted a structured approach for conducting end-to-end research experiments. The initial step involved the creation of tasks for participants and determining the sample size. In the second step, recruitment criteria were finalized. We recruited participants who were at least 18 years old and residents of the United States. Additionally, a fixed compensation of $4.00 for participant involvement is determined in this phase, which was crucial for attracting and retaining a representative sample. We also enabled participant payment criteria on prolific platform with the payment information. In the third step, we downloaded the raw data from Qualtrics platform for preliminary analysis. The preliminary analysis was designed to ensure the data was complete and accurate, making it ready for the next step of our research. In the fourth step of our study, we concentrated on ensuring the quality of our data. This stage involved verification checks and engagement through attention checks, confirming data uniqueness via duplication checks, and evaluating the efficacy of our experimental techniques through manipulation checks. The final step focused on the evaluation of the collected data. In this phase, measurement validation was performed to ascertain the accuracy of the instruments used in data collection. Finally, we conducted hypothesis testing to assess the relationships or effects that were posited at the outset of the research.

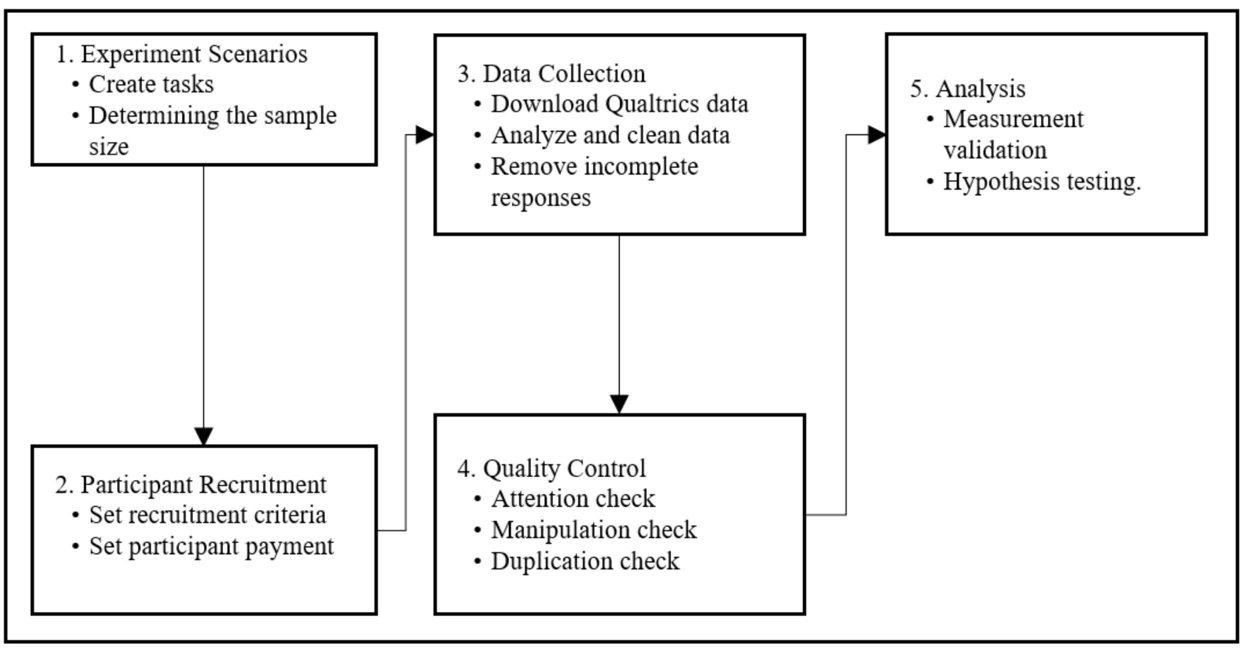


Figure 3 Experimental Flow

4.2. Task

Vignettes have been used to present experimental scenarios in the past Information Systems and management literature (O'Fallon and Butterfield, 2005; Goel et al., 2017; Johnston et al., 2016; Trinkle et al., 2014; Willison et al., 2018). This technique is particularly favored for its effectiveness in simulating real-life decision-making processes, allowing researchers to capture more nuanced insights into human behavior. Furthermore, the use of scenarios facilitates the exploration of hypothetical situations in a controlled environment, making it easier to isolate specific variables and study their impact on participants' responses. We employed a vignette-based research technique to explore the biases within e-commerce recommendation systems.

We employed a vignette-based research technique to explore the biases within e-commerce recommendation systems. Vignettes offer a structured and controlled method to examine customer opinions and behaviors within a simulated online purchasing environment (Flavián and Orús, 2020). This technique enabled us to introduce different bias scenarios in addition to the control scenario to different groups of participants. The use of vignettes was instrumental in eliciting participants' responses to different experiment scenarios. This methodology was chosen for its effectiveness in replicating real-world shopping experiences in a controlled experimental setting, thereby providing valuable insights into customer behavior and preferences in the context of recommendation system biases.

We recruited participants from the Prolific platform in the United States and presented them with four experiment scenarios (groups): popularity bias, sponsored bias, private-label bias, and a neutral (control) scenario as shown in Table 1.

Table 1 Experimental Design

Recommendation System Bias	Scenario
Popularity Bias	Scenario 1
Sponsored Bias	Scenario 2
Private Label Bias	Scenario 3
Neutral (control)	Scenario 4

The first treatment group (Group #1) was presented with a scenario involving popularity bias in product recommendations. Participants in this group were asked to envision a shopping experience dominated by "best-selling products," overshadowing their personalized preferences. The second treatment group (Group #2) encountered a scenario featuring sponsored products, where participants were prompted to imagine an e-commerce platform prioritizing “sponsored product”. The third treatment group (Group #3) was presented with a scenario involving preferential placement of private-label products—items sold by the platform or its affiliated companies. Lastly, group #4 functioned as the control group. In this scenario, users were presented with (unbiased) search results based solely on their preferences without any influence of recommendation system biases.

Table 2 Experiment Scenarios for Different Groups

Group	Experiment Scenario
Treatment Group#1 (Perception of Popular bias)	Consider that you are visiting an e-commerce platform (or website) for shopping. **You notice that the recommendation system used by the platform gives preference to "best-selling products" in its search results and not the products based on your preferences.** The term "best-selling products" refers to the items that have generated the highest sales volumes or revenue on online platforms over a period of time. These products demonstrate high demand and popularity among online shoppers. Considering this e-commerce platform in mind, answer the following questions.
Treatment Group#2 (Perception of sponsored bias)	Consider that you are visiting an e-commerce platform (or website) for shopping. **You notice that the recommendation system used by the platform gives preference to "sponsored products" in its search results and not the products based on your preferences.** The "Sponsored products" are items that sellers or brands pay to promote on the platform, increasing their visibility and chances of attracting customers. Considering this e-commerce platform in mind, answer the following questions.
Treatment Group#3 (Receives private-label bias)	Consider that you are visiting an e-commerce platform (or website) for shopping. **You notice that the recommendation system used by the platform gives preference to "private label products" (products sold under its own brand name of the platform/website) in its search results and not the products based on your preferences.** The "Private label products" are items that are sold under the e-commerce platform's brand name. Considering this e-commerce platform in mind, answer the following questions.
Treatment Group#4 Control Group (Receives no recommendation system bias)	Consider that you are visiting an e-commerce platform (or website) for shopping. **You notice that the recommendation system used by the platform presents you with a number of products in its search results based on your preferences.** Considering this e-commerce platform in mind, answer the following questions.

4.3. Sample Size

To ensure sufficient statistical power, our goal was to reach a minimum threshold of 0.8 (Cohen, 1988). To determine the optimal sample size, we employed three different approaches. First, we utilized the a-priori sample size calculator developed by Soper (2023), a tool that has gained widespread recognition in contemporary empirical research (Terlizzi et al., 2019; Ho et al., 2021; Masuch et al., 2020; Vance et al., 2022). Using input parameters of a medium effect size (0.3), the targeted statistical power (0.8), four latent variables, 22 observed variables, and a probability level 0.05, the calculator indicated that a minimum sample size of 138 was necessary.

Second, a power analysis was conducted utilizing the G*Power software to examine a between-subjects design (Ye and Kankanhalli, 2018; Chau et al., 2020). This analysis revealed that a sample of 126 participants would suffice to achieve the desired statistical power of 0.80. This conclusion was based on an anticipated effect size of 0.3, an alpha level of 0.05, numerator degrees of freedom (df) of 3, inclusion of four groups, and accounting for two covariates.

Third, to further refine our sample size estimation, we reviewed recent research in experimental methodologies related to recommendation system bias. For example, Wang et al., 2018 conducted a similar between-subject experiment involving 247 participants, distributed across six groups with a minimum of 40 participants each. Taking all these factors into account, we determined that a sample size of 240 would be appropriate for our study.

4.4. Data Collection

Our data collection process commenced after the approval from the university's Institutional Review Board (IRB). This step is essential to ensure that our research adheres to ethical guidelines and meets the established standards for research conduct. After receiving approval from the IRB, we constructed an online survey questionnaire using the Qualtrics platform. The survey questionnaire was then shared on the Prolific Panel platform with the participant pool. At the start of the survey, participants were presented with the consent form and those participants who agreed to the consent form were presented with the survey questionnaire.

We also leveraged an additional feature in Qualtrics[2] designed to detect and flag duplicate responses from participants. This feature is particularly useful in identifying and preventing instances where a single respondent might attempt to complete the survey multiple times. During the pilot phase, Qualtrics successfully identified and flagged a case of repetitive responses from the same IP address, which we excluded to ensure the data accuracy. In the main study, we activated this feature to prevent any repeated responses from participants, ensuring the uniqueness of each submission. This feature effectively ensured that no duplicates were found among the collected data.

4.5. Addressing Bots in Survey Research

During the pilot phase, our study encountered a noteworthy challenge with bot responses on the Prolific platform. Approximately 12% of our survey respondents were flagged as potential bot responses by the Qualtrics platform. Therefore, we implemented two strategies to tackle this issue and enhance our data's integrity in the main study.

[2] https://www.qualtrics.com/support/xm-discover/connectors/duplicate-detection/

At the onset of the survey, we integrated a reCAPTCHA verification question. The reCAPTCHA is designed to prevent automated bots from accessing the surveys. By requiring respondents to complete the reCAPTCHA question, we aimed to ensure that only human participants could proceed to the survey questionnaire. This step was crucial in safeguarding our survey from unauthorized and automated responses from bots.

4.6. Attention Check

In our study, we incorporated attention-check questions within the survey to guarantee the integrity and reliability of the responses from participants. For example, in the scenario addressing popularity bias, participants were prompted with the question, "Was the scenario related to 'best-selling products?" Similarly, in the context of sponsored bias, the question posed was, "Was the scenario related to 'sponsored products'?" In the scenario focusing on private-label bias, participants were asked, "Was the scenario related to 'private-label products'?" Finally, for the control group experiencing neutral recommendations, the question was structured as, "Was the scenario related to the e-commerce platform presenting products in its search results based on user preference?"

These attention-check questions aimed to identify participants who are not attentive or engaged with the survey content. Participants who inaccurately responded to these questions for their respective scenarios were flagged for providing potentially inattentive responses. This step was crucial in ensuring that our survey data remained free from the influence of disengaged or inattentive responses.

4.7. Manipulation Check

Our approach aligns with Oppenheimer et al. (2009), which supported the application of instructional manipulation checks (IMCs). This method identifies and removes responses from participants who respond without paying enough attention to the experiment. In our study, we incorporated manipulation checks to validate the effectiveness of our experimental manipulations. These checks were crucial in enhancing the study's internal validity (Kung et al., 2018). See Table 3 for manipulation check questions.

Following the presentation of each experiment scenario, we administered manipulation check questions. This immediate follow-up with manipulation test questions (Table 3) was crucial in ensuring that the manipulations have the intended effect and thereby supporting the validity and reliability of the study's conclusions.

Table 3 Manipulation Check Questions

Manipulation Check	Questions
Manipulation Check 1	Please indicate your level of agreement with the following statement: The e-commerce platform presented in the previous scenario would recommend products based on your preferences.
Manipulation Check 2 (Wang et al., 2019)	Please indicate your level of agreement with the following statements: 1. This recommendation system appears to be biased toward certain products. 2. This recommendation system provides misleading recommendations. 3. When giving recommendations, this recommendation system distorts factors in favor of certain products.

A crucial element of our manipulation checks was the implementation of a response timer (Paas et al.,2018). This tool assessed whether participants allocated sufficient time to read and comprehend the scenario before answering the questions. The response timer was an objective measure to determine if participants effectively processed the treatment information as intended.

4.8. Constructs

We carefully adapted measurement items from previous established scales, modifying them to fit the reliability criteria of our study, as detailed in Table 4 (Lee et al., 2011; Shin, 2021; Wang et al., 2018). Specifically, for assessing perceived fairness, we adapted items from Shin (2021). Shin's study examined perceptions of fairness in a context similar to ours, providing an exceptionally relevant foundations for our research questions. In measuring distrust, particularly in the context of recommendation systems, we employed the distrust scale developed by Wang et al. (2018). This scale has been previously validated and found to be reliable for measuring customers' distrust towards recommendation systems. For the measurement of equity sensitivity, we adopted the scale developed by Kings and Miles (1987). Lastly, to measure exchange ideology, we applied the scale developed by Scott and Colquitt (2007). Responses were collected using a seven-point Likert scale to measure the degree of participants' agreement or disagreement with each question (item). We chose a 7-point Likert scale for our survey because it offers respondents a broader range of options compared to a more limited scale like a 5-point one (Joshi et al., 2015). This scale ranged from "strongly disagree" (1) through a neutral option of "neither agree nor disagree" (4) to "strongly agree" (7). Utilizing this scale allowed for a detailed insight into the attitudes and perceptions of the participants (Kreitchmann et al., 2019). The definitions of the constructs used in our research with their references are presented in Table 4.

Table 4 Measurement Constructs

Construct	Definition	References
Perceived Fairness	Perceived fairness is a psychological construct that reflects a person's perception of whether they have been treated fairly or unfairly based on their expectations, values, and social norms.	Lee et al., (2011); Shin, (2021)
Distrust	Distrust is the opposite of trust and refers to a lack of belief, confidence, or faith in a person, organization, or system.	Wang et al., (2018)
Equity Sensitivity	Equity sensitivity refers to the extent to which individuals are responsive to imbalances between outcomes and inputs. Those who fall on the entitled end of the equity sensitivity continuum are highly sensitive to relative outcome levels, while those on the benevolent end are less affected by them.	Kings and Miles (1987)
Exchange Ideology	Exchange ideology encompasses the individual's mindset and expectations regarding reciprocity, fairness, and the social give-and-take in relationships within the organizational context.	Scott and Colquitt (2007)

Chapter 5. Data Analysis and Findings

5.1. Data Collection

The recruitment method for our study was customized to align with our research objectives, particularly focusing on individuals who had previous experience with e-commerce. A diverse group of 269 participants, representing a wide range of demographic backgrounds as detailed in Table 5. Additionally, we selected participants of United States nationality to ensure cultural homogeneity in shopping behaviors. Participants were surveyed regarding the number of times they engaged in online shopping within a month.

Our data shows a diverse range of e-commerce platform experiences among participants: 62% with over ten years, 17% between five to ten years, 12% for two to five years, 6% with one to two years, and 3% less than a year. This distribution indicates that a considerable portion of our surveyed individuals were experienced e-commerce users. The age distribution of our participant pool was as follows: the median age was around 40 years, and the gender distribution included 58% females, 41% males, and 1% identifying as non-binary. The sample population shows a relatively uniform age distribution, comprising 51% of participants aged 41 and above and the remaining 49% under the age of 41.

Table 5 Demographic Background of Experimental Participants

Variable/ item		No. of participants (%)
Gender	Male	109 (41%)
	Female	156 (58%)
	Non-Binary	4 (1%)
Age	Under 20	-
	21 to 25	8 (3%)
	26 to 30	51 (19%)
	31 to 35	30 (11%)
	36 to 40	42 (16%)
	Over 41	138 (51%)
Experience in using e-commerce (years)		
	Less than 1	7 (3%)
	1 to 2	15 (6%)
	2 to 5	33 (12%)
	5 to 10	47 (17%)
	More than 10	167 (62%)
Percentage (%) of monthly shopping budget spent on online shopping platforms	0 to 10	39 (14%)
	10 to 25	77 (29%)
	25 to 50	66 (25%)
	50 to 75	51 (19%)
	Above 75	36 (13%)
E-commerce Platform used most frequently.	Amazon	204 (76%)
	Walmart	19 (7%)
	eBay	13 (5%)
	Shopify	13 (5%)
N = 269		

The participants also provided information about the budget they allocate for shopping on various e-commerce sites. A small percentage of individuals (14%) spend 0-10% of their monthly budget on online shopping. The majority (29%) allots a moderate portion of their monthly purchasing budget—between 10% and 25%—on e-commerce. 25% of the respondents spend between 25% and 50% of their budget on online shopping. Approximately 19% of the participants are frequent online buyers, allocating 50% to 75% of their budget on e-commerce. Finally, 13% of the participants spend over 75% of their buying money on online shopping platforms.

Interestingly, there was a predominant preference for shopping on Amazon, with 76% of participants indicating it as their most frequently used e-commerce platform of choice. Furthermore, we also gathered data on the usage percentages of other e-commerce platforms among our participants. Specifically, Walmart, eBay, and Shopify were used by 7%, 5%, and 5% of our participants, respectively. This information highlights our participants' distinct preference for Amazon, pointing to its significant market dominance compared to other platforms.

We used IBM SPSS (Statistical Package for the Social Sciences) Statistics 29 and SPSS AMOS software for statistical analysis. Both of these statistical tools are part of the SPSS suite and are widely recognized for their capabilities in statistical analysis and modeling. The IBM SPSS software offers a broad range of statistical analysis capabilities, including but not limited to descriptive statistics, regression analysis, ANOVA, factor analysis, and time series analysis (George and Mallery, 2019). Similarly, SPSS AMOS is a comprehensive toolset designed for structural equation modeling (SEM), enabling researchers to easily specify, estimate, assess, and present models to show hypothesized relationships among variables. As a preliminary step, we measured all variables' means, standard deviations, correlations, and reliability (Table 14 and Table 21).

5.2. Manipulation checks

Table 6 presents two checks designed to verify the effectiveness of the four experimental scenarios presented in the previous chapter. These checks were crucial in assessing how participants differentiated various bias scenarios with respect to the neutral (control) scenario.

Table 6 Manipulation Check 1 and 2 – Summary Statistics

		Manipulation Check 1		Manipulation Check 2	
Scenario	N	Mean	Std. Deviation	Mean	Std. Deviation
Popularity Bias	69	5.48	1.389	5.20	1.419
Sponsored Bias	68	5.28	1.413	5.89	1.259
Private-Label Bias	67	5.60	1.558	5.98	1.164
Neutral (control)	65	6.52	.664	3.56	1.507
Total	269	5.71	1.384	5.17	1.645

The first manipulation check (Manipulation Check 1) measured participants' perception of whether the recommendation system suggests products based on their preferences in each of the four scenarios. As per Table 6 , the neutral scenario scored higher compared to the biased scenarios. This significant difference effectively highlights the distinction in participants' perceptions across the neutral and biased scenarios. We utilized ANOVA (analysis of variance) to evaluate the mean differences for manipulation check 1 as shown in Table 7. The ANOVA results indicated a statistically significant difference between the groups (F statistics = 11.721; df = 3; p <.001). In addition, we conducted a post-hoc test to analyze the differences among these groups. These tests, including Tukey HSD, Scheffe, and Bonferroni, are summarized in

Table 8. Compared to the control group (#4), the participants in biased groups perceived the recommendation system suggesting products of lower preference.

Table 7 ANOVA for Manipulation Check 1

ANOVA					
Manipulation Check 1					
	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	60.140	3	20.047	11.721	<.001
Within Groups	453.243	265	1.710		
Total	513.383	268			

Table 8 Group Differences for Manipulation Check 1

Dependent Variable: Manipulation Check 1							
						95% Confidence Interval	
	(I) Scenario	(J) Scenario	Mean Difference (I-J)	Std. Error	Sig.	Lower Bound	Upper Bound
Tukey HSD	1	2	.199	.223	.810	-.38	.78
		3	-.119	.224	.952	-.70	.46
		4	-1.045*	.226	<.001	-1.63	-.46
	2	1	-.199	.223	.810	-.78	.38
		3	-.318	.225	.494	-.90	.26
		4	-1.244*	.227	<.001	-1.83	-.66
	3	1	.119	.224	.952	-.46	.70
		2	.318	.225	.494	-.26	.90
		4	-.926*	.228	<.001	-1.51	-.34
	4	1	1.045*	.226	<.001	.46	1.63
		2	1.244*	.227	<.001	.66	1.83
		3	.926*	.228	<.001	.34	1.51
Scheffe	1	2	.199	.223	.851	-.43	.83

		3	-.119	.224	.964	-.75	.51
		4	-1.045*	.226	<.001	-1.68	-.41
	2	1	-.199	.223	.851	-.83	.43
		3	-.318	.225	.575	-.95	.32
		4	-1.244*	.227	<.001	-1.88	-.61
	3	1	.119	.224	.964	-.51	.75
		2	.318	.225	.575	-.32	.95
		4	-.926*	.228	.001	-1.57	-.29
	4	1	1.045*	.226	<.001	.41	1.68
		2	1.244*	.227	<.001	.61	1.88
		3	.926*	.228	.001	.29	1.57
Bonferroni	1	2	.199	.223	1.000	-.40	.79
		3	-.119	.224	1.000	-.72	.48
		4	-1.045*	.226	<.001	-1.65	-.44
	2	1	-.199	.223	1.000	-.79	.40
		3	-.318	.225	.957	-.92	.28
		4	-1.244*	.227	<.001	-1.85	-.64
	3	1	.119	.224	1.000	-.48	.72
		2	.318	.225	.957	-.28	.92
		4	-.926*	.228	<.001	-1.53	-.32
	4	1	1.045*	.226	<.001	.44	1.65
		2	1.244*	.227	<.001	.64	1.85
		3	.926*	.228	<.001	.32	1.53
*. The mean difference is significant at the 0.05 level.							

The second manipulation check (Manipulation Check 2) measured recommendation neutrality with reversed coded items. The participants in the control group noted stronger recommendation neutrality in comparison to the bias groups. This difference further substantiates the efficacy of our scenario manipulations. A similar ANOVA analysis for Manipulation Check 2 was significant (F statistics = 45.690; df = 3; $p < .001$) as presented in Table 9. Further, the participants in the control group (group#4) found the recommendation system more neutral compared to those in biased groups (see Table 10).

Table 9 ANOVA for Manipulation Check 2

ANOVA					
Manipulation Check 2					
	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	247.170	3	82.390	45.690	<.001
Within Groups	477.856	265	1.803		
Total	725.025	268			

Table 10 Group Differences for Manipulation Check 2

Dependent Variable: Manipulation Check 2						95% Confidence Interval	
	(I) Scenario	(J) Scenario	Mean Difference (I-J)	Std. Error	Sig.	Lower Bound	Upper Bound
Tukey HSD	1	2	-.68919*	.22946	.015	-1.2824	-.0959
		3	-.77706*	.23032	.005	-1.3725	-.1816
		4	1.63909*	.23211	<.001	1.0390	2.2392
	2	1	.68919*	.22946	.015	.0959	1.2824
		3	-.08787	.23115	.981	-.6855	.5098
		4	2.32828*	.23294	<.001	1.7260	2.9305
	3	1	.77706*	.23032	.005	.1816	1.3725
		2	.08787	.23115	.981	-.5098	.6855
		4	2.41615*	.23379	<.001	1.8117	3.0206
	4	1	-1.63909*	.23211	<.001	-2.2392	-1.0390
		2	-2.32828*	.23294	<.001	-2.9305	-1.7260
		3	-2.41615*	.23379	<.001	-3.0206	-1.8117
Scheffe	1	2	-.68919*	.22946	.031	-1.3348	-.0436
		3	-.77706*	.23032	.011	-1.4251	-.1290
		4	1.63909*	.23211	<.001	.9860	2.2921
	2	1	.68919*	.22946	.031	.0436	1.3348
		3	-.08787	.23115	.986	-.7382	.5625
		4	2.32828*	.23294	<.001	1.6729	2.9837
	3	1	.77706*	.23032	.011	.1290	1.4251
		2	.08787	.23115	.986	-.5625	.7382
		4	2.41615*	.23379	<.001	1.7584	3.0739
	4	1	-1.63909*	.23211	<.001	-2.2921	-.9860
		2	-2.32828*	.23294	<.001	-2.9837	-1.6729
		3	-2.41615*	.23379	<.001	-3.0739	-1.7584
Bonferroni	1	2	-.68919*	.22946	.018	-1.2991	-.0792

		3	-.77706*	.23032	.005	-1.3893	-.1648
		4	1.63909*	.23211	<.001	1.0221	2.2561
	2	1	.68919*	.22946	.018	.0792	1.2991
		3	-.08787	.23115	1.000	-.7023	.5266
		4	2.32828*	.23294	<.001	1.7091	2.9475
	3	1	.77706*	.23032	.005	.1648	1.3893
		2	.08787	.23115	1.000	-.5266	.7023
		4	2.41615*	.23379	<.001	1.7947	3.0376
	4	1	-1.63909*	.23211	<.001	-2.2561	-1.0221
		2	-2.32828*	.23294	<.001	-2.9475	-1.7091
		3	-2.41615*	.23379	<.001	-3.0376	-1.7947
*. The mean difference is significant at the 0.05 level. Note: The items are reverse coded.							

To accurately evaluate participant engagement, we closely observed the time participants spent on each scenario. Our findings indicated that participants were involved with the popularity bias scenario for an average duration of 73 seconds, the sponsored bias scenario for 47 seconds, the private-label bias scenario for 42 seconds, and the neutral bias scenario for 27 seconds. The variations in the use of time indicate varying levels of engagement, with the popularity bias scenario receiving the highest level of attention. The variation in attention durations between scenarios supports the notion that participants were attentive and actively engaged in understanding and responding to the scenarios provided.

5.3. Attention Checks

In our survey, we observed that not all the 283 participants were fully engaged with the survey questions. We identified five participants who did not complete the survey. Additionally, nine individuals, which constituted approximately 3% of our total sample, failed to meet the criteria set by our attention check questions (Table 11). In the process of analyzing our data, we identified that three participants from the private-label group and six from the neutral group failed to pass the necessary attention checks. This led to a final count of 269 valid responses, all from participants who successfully passed the attention check, thus providing a robust and reliable data set for our subsequent analysis. As highlighted in the Table 11, all 72 participants in the first group accurately answered the attention check question. Similarly, in the Sponsored Bias group, all 68 participants correctly recognized the scenario's related to "sponsored products." However, in the Private-label Bias group, 3 out of 70 participants failed to identify the scenario correctly, and in the Neutral (Control) group, 6 out of 71 participants did not pass the attention check. This suggests varying levels of participant engagement or understanding across different scenarios.

Table 11 Attention Check Questions for Survey Questionnaire

Scenario (Group)	**Attention check question**	**Raw data**	**Incomplete/ failed attention**	**Qualified**
Popularity Bias	Was the scenario related to "best-selling products"?	72	3/0	69
Sponsored Bias	Was the scenario related to "sponsored products"?	69	1/0	68
Private-label Bias	Was the scenario related to "private-label products"?	71	1/3	67
Neutral (Control)	Was the scenario related to the e-commerce platform presenting number of products in its search results based on user preference?	71	0/6	65
Total		283	14	**269**

5.4. Measurement Validation

We conducted an Exploratory Factor Analysis (EFA) to assess the foundational constructs influencing participant responses and to pinpoint any items that were redundant or irrelevant. This step is crucial in ensuring the validity and reliability of our measurement scales. Utilizing Varimax rotation with Kaiser Normalization during the

EFA, we observed that certain items demonstrated low or weak factor loadings (Table 12). Specifically, items under the constructs of Perceived Fairness (PF2), Equity Sensitivity (ES22), and two items from exchange ideology (EI1 and EI2) exhibited these weaker loadings. These low factor loadings suggest that these items contributed little to the constructs they were intended to measure. As a result, we made a methodologically informed decision to remove these items from further analysis. The removal of PF2, ES22, EI1, and EI2 was a critical step in refining our measurement scales, adhering to the principle that scale items should closely correspond with the construct they represent. This elimination was aimed at improving the overall construct validity of our scales, ensuring that each construct is precisely and robustly reflected in our analysis.

Table 12 Removed Items

Construct	Item No.	Item
Perceived Fairness	PF2	The source of data throughout the recommendation system and its data sources should be identified, logged, and benchmarked (Shin, 2021)
Equity Sensitivity	ES22	It would be more important for me to watch out for my own good (King & Miles, 1994)
Exchange Ideology	EI1	An employee's work effort should depend partly on how well the organization deals with his or her desires and concerns (Scott & Colquitt, 2007)
Exchange Ideology	EI2	An employee who is treated badly by the organization should lower his or her work effort (Scott & Colquitt, 2007)

We utilized the Principal Component Analysis (PCA) as the extraction method in our analysis as indicated in the Table 13. This choice was driven by PCA's effectiveness in identifying the underlying factor structure of the data. We implemented a Varimax rotation coupled with Kaiser Normalization to enhance our analysis further. Our study found that each item had greater loadings on their corresponding constructs compared to any other constructs, showing an effective alignment with the desired factor structure. The results validate the distinctiveness of each construct, as all items specifically created to assess a particular construct consistently loaded onto a single factor. Moreover, the disparities between the loadings of individual items and their loadings on other factors were greater than 0.10, which establishes discriminant validity.

Table 13 EFA Factor Loading

Rotated Component Matrix[a]				
	Component			
	1	2	3	4
PF1	-.328	**.830**	-.033	-.073
PF3	-.250	**.860**	-.071	-.148
PF4	-.280	**.804**	-.083	-.141
PF5	-.424	**.798**	-.071	-.076
PF6	-.274	**.836**	.032	-.065
PF7	-.363	**.839**	-.082	-.116
ES11	.055	-.103	**.826**	-.005
ES31	.104	.040	**.845**	.116
ES42	.085	-.001	**.784**	.200
ES51	.080	-.109	**.725**	.166
EI3 (R)	-.021	-.132	.098	**.835**
EI4 (R)	.016	-.090	.153	**.811**
EI5 (R)	.101	-.138	.191	**.791**
DIST1	**.850**	-.274	.105	.046
DIST2	**.858**	-.211	.023	-.012
DIST3	**.832**	-.249	.048	.058
DIST4	**.813**	-.400	.065	-.006
DIST5	**.792**	-.283	.050	.004
DIST6	**.864**	-.193	.045	.035
DIST7	**.877**	-.162	.091	.082
DIST8	**.845**	-.303	.102	.044
DIST9	**.797**	-.292	.137	.008
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.				
a. Rotation converged in 6 iterations.				

This comprehensive factor analysis in our study served a dual purpose: it validated the constructs and confirmed that the measures used were robust and well-aligned with our research objectives. The use of Principal Component Analysis (PCA) and the subsequent rotation method were key in enhancing the clarity and interpretability of our factor structure, thereby playing a critical role in the overall success of our study's analytical approach.

5.5. Measurement Characteristics

Our study involved a thorough assessment of the reliability and validity of our measurement scales. To evaluate reliability, we employed Cronbach's alpha coefficient, with the results presented in Table 14. All the values we obtained exceeded the 0.7 benchmark, consistent with the standards set by Nunnally and Bernstein (1994). These high Cronbach's alpha values across our scales signify a robust internal consistency and reliability of the items within each construct. To assess the possibility of common method bias, Harman's single-factor test was employed. This test's findings indicated that the percentages of variance explained by a single factor were 35.47%. Since these values are all below the 50% threshold, it suggests that common method bias is not present in the data.

To assess discriminant validity, we employed two recognized criteria: firstly, by comparing the square root of the Average Variance Extracted (AVE) of each construct against its correlations with all other constructs, as detailed in Table 12. This criterion helps ensure that each construct is distinct and captures unique variance. Second, we confirmed that each item correlated more with its intended construct than with any other construct, as Barclay et al. (1995) suggested. Our analysis confirmed the discriminant validity of our measurement scales, indicating that the constructs are sufficiently distinct from each other.

Table 14 Descriptive Statistics: Correlation, and Reliability

	Correlation						
Variable	1	2	3	4	CA	AVE	CR

1. Perceived Fairness	**0.83**				0.95	0.68	0.93
2. Equity Sensitivity	-0.16	**0.78**			0.82	0.60	0.86
3. Exchange Ideology	-0.28	0.41	**0.81**		0.79	0.66	0.85
4. Distrust	-0.60	0.20	0.26	**0.84**	0.96	0.70	0.93
Notes: CA: Cronbach’s Alpha (>0.7) (Nunnally and Bernstein 1994) AVE: Average Variance Extracted (>0.5) (Fornell and Larcker, 1981, p.46) CR: Composite Reliability (>0.7) (Nunnally and Bernstein 1994) The values on the principal diagonal presented in the above correlation matrix represent square roots of AVEs. The value of the square root of the AVE of every construct is greater than intercorrelation (Fornell and Larcker, 1981)							

We also evaluated the convergent validity of our constructs by analyzing the Average Variance Extracted (AVE), in line with Fornell and Larcker (1981)'s guidelines. The AVE values for each construct surpassed the 0.5 threshold, demonstrating satisfactory convergent validity. To further strengthen the robustness of our measurement model, Composite Reliability (CR) was calculated, adhering to the methodology recommended by Nunnally and Bernstein (1994), with the minimum acceptable value being 0.7. Moreover, a review of the correlation matrix showed that the square roots of the AVEs matched the values on the principal diagonal, further confirming the validity of the average variance extracted for each construct.

To establish discriminant validity, we followed the criterion set by Fornell and Larcker (1981), ensuring that the square root of the Average Variance Extracted (AVE) for each construct was greater than its intercorrelations with other constructs. The methods used in assessing reliability and validity in our study highlight the strength and consistency of our measurement framework.

In Exploratory Factor Analysis (EFA), the 'Total Variance Explained' is a key measure that indicates the proportion of the dataset's variance accounted for by the factors extracted, as shown in Table 15. In our study, the exploratory factor analysis (EFA) identified four distinct components within our data. Collectively, these components account for 75.753% of the total variance, indicating a substantial proportion of the dataset's variability is captured by these factors. This significant level of explained variance underscores the relevance and robustness of the identified components in our analysis.

Table 15 EFA Variance Extracted

Total Variance Explained									
Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	9.964	45.289	45.289	9.964	45.289	45.289	6.978	31.717	31.717
2	2.973	13.512	58.801	2.973	13.512	58.801	4.847	22.032	53.749
3	2.312	10.509	69.311	2.312	10.509	69.311	2.691	12.233	65.981
4	1.417	6.443	75.753	1.417	6.443	75.753	2.150	9.772	75.753
5	.666	3.026	78.780						
6	.605	2.751	81.530						
7	.511	2.321	83.852						
8	.407	1.852	85.704						
9	.346	1.573	87.276						
10	.334	1.517	88.794						
11	.302	1.374	90.168						
12	.287	1.305	91.473						
13	.264	1.202	92.675						
14	.242	1.099	93.774						
15	.232	1.055	94.829						
16	.207	.942	95.771						
17	.193	.877	96.647						
18	.176	.799	97.446						
19	.164	.744	98.190						
20	.153	.696	98.886						
21	.131	.597	99.483						
22	.114	.517	100.000						

Extraction Method: Principal Component Analysis.

Table 16, the correlation matrix, displays the relationships among various variables. This matrix highlights the degrees of association between different factors and indicators within our data. The table clearly denotes the significance levels of these correlations, marked with p-values of less than 0.05 and 0.01. In this study, we observed no significant correlations between any pair of items originating from distinct constructs. This lack of high correlation highlights the independence of the constructs within our study, reinforcing the distinctiveness of each measurement domain. This finding is crucial for validating the theoretical framework that delineates these constructs as separate entities.

Table 16 Item Correlation Matrix

		1	2	3	4	5	6	7	9	10	11	12	13
1	PF1	--											
2	PF3	.75**	--										
3	PF4	.72**	.75**	--									
4	PF5	.78**	.77**	.77**	--								
5	PF6	.76**	.75**	.70**	.74**	--							
6	PF7	.81**	.85**	.74**	.81**	.76**	--						
7	ES11	-.16*	-.14*	-.14*	-.14*	-.08	-.16**	--					
8	ES31	-.04	-.07	-.09	-.09	0	-.1	.61**	--				
9	ES42	-.09	-.12	-.14*	-.13*	-.01	-.11	.50**	.65**	--			
10	ES51	-.1	-.20**	-.18**	-.17**	-.1	-.20**	.53**	.48**	.48**	--		
11	EI3 (R)	-.17**	-.21**	-.25**	-.15*	-.16**	-.19**	.17**	.18**	.18**	.23**	--	
12	EI4 (R)	-.16**	-.22**	-.16**	-.14*	-.13*	-.22**	.18**	.23**	.27**	.20**	.58**	--
13	EI5 (R)	-.21**	-.28**	-.27**	-.26**	-.18**	-.24**	.12*	.24**	.34**	.32**	.56**	.51**

14	DIST1	-.51**	-.46**	-.48**	-.57**	-.48**	-.55**	.17**	.14*	.16*	.20**	.05	.11
15	DIST2	-.49**	-.40**	-.42**	-.53**	-.38**	-.48**	.1	.1	.12*	.08	.01	.03
16	DIST3	-.46**	-.44**	-.47**	-.59**	-.42**	-.51**	.08	.15*	.14*	.13*	.07	.06
17	DIST4	-.59**	-.54**	-.55**	-.67**	-.53**	-.63**	.16**	.1	.08	.20**	.08	.04
18	DIST5	-.48**	-.44**	-.47**	-.59**	-.45**	-.50**	.08	.13*	.16*	.11	.04	.03
19	DIST6	-.45**	-.41**	-.39**	-.49**	-.43**	-.51**	.14*	.12*	.08	.14*	.06	.07
20	DIST7	-.44**	-.39**	-.39**	-.49**	-.42**	-.47**	.17**	.15*	.15*	.17**	.07	.11
21	DIST8	-.53**	-.49**	-.49**	-.60**	-.49**	-.60**	.14*	.17**	.16**	.20**	.04	.11
22	DIST9	-.51**	-.45**	-.45**	-.58**	-.45**	-.56**	.20**	.19**	.15*	.18**	.06	.07

		13	14	15	16	17	18	19	20	21	22
13	EI5 (R)	--									
14	DIST1	.18**	--								
15	DIST2	.11	.75**	--							
16	DIST3	.18**	.75**	.76**	--						
17	DIST4	.13*	.79**	.77**	.77**	--					
18	DIST5	.14*	.71**	.75**	.78**	.76**	--				
19	DIST6	.12	.78**	.74**	.72**	.75**	.66**	--			
20	DIST7	.19**	.79**	.74**	.70**	.75**	.66**	.81**	--		
21	DIST8	.17**	.80**	.72**	.73**	.79**	.70**	.81**	.85**	--	
22	DIST9	.15*	.76**	.72**	.70**	.76**	.66**	.71**	.75**	.75**	--

**Correlation is significant at the 0.01 level (2-tailed).

* Correlation is significant at the 0.05 level (2-tailed).

Listwise N=269

Notes: PF: Perceived Fairness; ES: Equity Sensitivity; EI: Exchange Ideology; (R): Reverse Coded Item; DIST: Distrust

Table 17 Descriptive Statistics of Items

Item	N	Mean	Standard Deviation
PF1	269	3.27	1.79
PF3	269	3.01	1.82
PF4	269	3.42	1.77
PF5	269	3.49	1.80
PF6	269	3.25	1.81
PF7	269	3.12	1.76
ES11	269	6.28	2.10
ES31	269	5.88	2.21
ES42	269	5.55	2.44
ES51	269	5.78	2.61
EI3 (R)	269	4.73	1.76
EI4 (R)	269	4.85	1.76
EI5 (R)	269	4.59	1.84
DIST1	269	4.48	1.82
DIST2	269	4.11	1.84
DIST3	269	4.07	1.80
DIST4	269	4.48	1.81
DIST5	269	3.93	1.80
DIST6	269	4.60	1.81
DIST7	269	4.65	1.84
DIST8	269	5.03	1.79
DIST9	269	4.65	1.97

Table 18 in our study summarizes the standardized loadings for various items on their respective constructs and Table 17 presents the average values and their standard deviation. shows that items PF7, PF6, PF5, PF4, PF3, and PF1 related to the Perceived Fairness (PF) construct, have significant standardized loadings above 0.7, indicating a strong correlation with the PF construct. Similarly, the equity sensitivity (ES) construct shows significant loadings for items ES51, ES42, ES31, and ES11, reflecting a strong association with these items.

For the exchange ideology (EI) construct, items EI5 (R), EI4 (R), and EI3 (R) shows stable standardized loadings. The Distrust (DIST) construct is well-represented by items DIST9, DIST8, DIST7, DIST6, DIST5, DIST4, DIST3, DIST2, and DIST1, each demonstrating substantial positive loadings with the construct. This breakdown provides clear insights into the strength of associations between particular items and their corresponding constructs, facilitating statistical analysis.

The confirmatory factor analysis as shown in Table 18 highlights strong model fit statistics, indicating the high reliability of our model. All standardized loadings above the criterion of 0.6, indicating a high level of item reliability. The validity of the model is supported by a Chi-square value of 436.94, with 203 degrees of freedom. The Chi-square to degrees of freedom ratio is 2.15, which falls comfortably within the permissible range of less than 3. In addition, the Comparative Fit Index (CFI) has a value of 0.95, which exceeds the recommended threshold of 0.9. In addition, the Root Mean Square Error of Approximation (RMSEA) is 0.066, substantially below the cutoff of 0.08. These results indicate a satisfactory fit according to the criteria established by Thatcher et al. (2018).

On the other hand, the single-factor model shows a less satisfactory fit, shown by a Chi-square value of 1997.52 for 209 degrees of freedom. The Chi-square difference between the suggested model and the single-factor model is a statistically significant 1560.58, with a change of 6 degrees of freedom. This indicates a considerable improvement in the fit of the proposed model compared to the single-factor model ($p < .05$). In addition, all standardized item loadings in the multi-factor model are statistically significant at a significance level of $p < .01$, which further confirms the statistical strength of the factor structure.

Table 18 CFA Standardized Loadings

Item	Construct	Standardized Loadings
PF7	PF	.923
PF6	PF	.838
PF5	PF	.889
PF4	PF	.826
PF3	PF	.886
PF1	PF	.874
ES51	ES	.635
ES42	ES	.757
ES31	ES	.830
ES11	ES	.723
EI5 (R)	EI	.729
EI4 (R)	EI	.731
EI3 (R)	EI	.769
DIST9	DIST	.839
DIST8	DIST	.899
DIST7	DIST	.879
DIST6	DIST	.869
DIST5	DIST	.814
DIST4	DIST	.892
DIST3	DIST	.844
DIST2	DIST	.854
DIST1	DIST	.891

Note: All standardized loadings are > 0.6; Chi-square = 436.94; df = 203

Chi-square/ df = 2.15 (Should be < 3); CFI = 0.95 (Should be > 0.9); RMSEA = 0.066 (Should be < 0.08) (Thatcher et al., 2018)

Chi-square = 1997.52; df = 209 (for single factor model)

Chi-square = 1560.58; df = 6 (significant at p < .05)

PF: Perceived Fairness; ES: Equity Sensitivity; EI: Exchange Ideology; (R): Reverse Coded Item; DIST: Distrust

All standardized item loadings are significant at p < .01.

As shown in Figure 4, high factor loadings in our analysis indicate that each set of indicators reliably measures its corresponding latent variables. The data clearly shows a strong negative association of -0.60 between Perceived Fairness and Distrust. This suggests that when the perception of fairness declines, distrust rises. In addition, we noticed a direct relationship between equity sensitivity and exchange ideology, indicating that persons with a higher sensitivity to fairness are more inclined to support exchanging goods or services. These findings enhance our understanding of how individual traits and fairness perceptions interact within the study context.

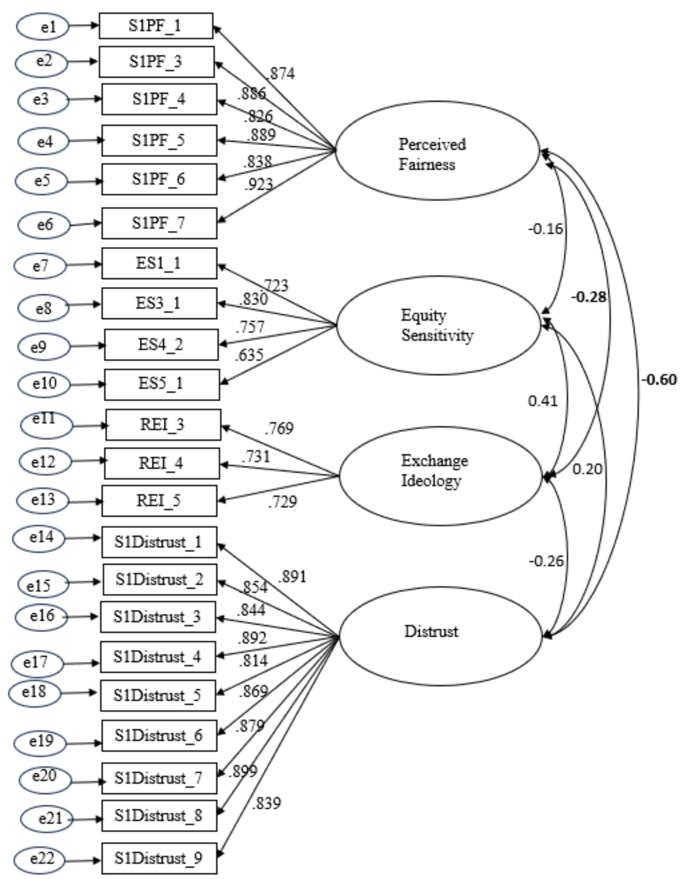


Figure 4 CFA Diagram

5.6. Hypothesis Testing Results

To test the hypothesized impact of popularity bias, sponsored bias, private-label bias, and neutral recommendations on perceived fairness (as outlined in hypotheses H1a, H1b, H1c, and H1d), we conducted an Analysis of Covariance (ANCOVA), using perceived fairness as the dependent variable, as shown in Table 19. The analysis shows a statistically significant effect of the neutrality of recommendations on perceived fairness ($p < .001$).

Further insights are provided by the descriptive statistics in Table 20. These statistics suggest that customers exposed to popularity bias in a recommendation system perceive it as less fair compared to those who do not encounter such bias, supporting H1a. Similarly, exposure to sponsored bias (supporting H1b) and private-label bias (supporting H1c) leads customers to perceive the recommendation system as less fair than those who do not face such biases. Additionally, the results support H1d by indicating that customers experience popularity bias as more fair than those facing sponsored or private-label biases.

Table 19 provides a more detailed analysis of parameter estimates related to the perception of fairness. The intercept, which indicates the estimated level of Perceived Fairness when all other variables are at zero, has been found to be statistically significant ($p < 0.001$) at a value of 359.111. While equity sensitivity does not significantly impact perceived fairness ($F = .053$, $p = 0.817$), exchange ideology shows a significant negative effect ($F = 18.719$, $p < 0.001$). It implies that an increase in exchange ideology is associated with a decrease in Perceived Fairness.

Table 19 ANCOVA Results for Perceived Fairness

Tests of Between-Subjects Effects						
Dependent Variable: Perceived Fairness						
Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared

Corrected Model	174.315[a]	5	34.863	25.944	<.001	.330
Intercept	359.111	1	359.111	267.243	<.001	.504
e	.072	1	.072	.053	.817	.000
Exchange Ideology	25.154	1	25.154	18.719	<.001	.066
Scenario	132.488	3	44.163	32.865	<.001	.273
Error	353.410	263	1.344			
Total	3871.653	269				
Corrected Total	527.725	268				
a. R Squared = .330 (Adjusted R Squared = .318)						

Table 20 showcases the means and standard deviations for constructs across different experimental groups. To examine the impact of equity sensitivity (H2a) and exchange ideology (H2b) on perceived fairness as moderating factors, an ANCOVA was performed. In this analysis, perceived fairness served as the dependent variable, with popularity bias, sponsored bias, and private-label bias acting as control variables. As shown in Table 20, the ANCOVA outcomes confirm the significance of the interaction term between perceived fairness (dependent variable, DV) and equity sensitivity (covariate). Similarly, the findings from the ANCOVA analysis reported in this table highlight the significance of the interaction term between perceived fairness (DV) and exchange ideology (covariate). Hypothesis 2a and 2b are supported by the fact that the perceived fairness of recommendation systems is significant for customers with equity sensitivity and exchange ideology. The results reported in this table indicate that bias in a recommendation system led to a higher level of distrust than in a neutral recommendation system, thus supporting H3. Support for Hypotheses H1a, H1b, H1c, and H1d showed that users of a recommendation system who encountered different biases found the system less fair than users who were not exposed to those biases. Evidence also confirmed Hypotheses H2a and H2b, demonstrating that customers with high levels of exchange ideology and equity sensitivity perceived recommendation systems as less fair compared to those with lower levels of these traits.

Furthermore, support was found for Hypothesis H3, indicating that perceived fairness negatively influenced perceived distrust. These findings provide valuable insights into the correlation between bias perception, individual traits, and distrust in recommendation systems within the e-commerce context.

Table 20 ANCOVA Parameters for Perceived Fairness

Parameter Estimates							
Dependent Variable: Perceived Fairness							
					95% Confidence Interval		
Parameter	B	Std. Error	t	Sig.	Lower Bound	Upper Bound	Partial Eta Squared
Intercept	5.870	.310	18.941	<.001	5.260	6.480	.577
Equity Sensitivity	-.010	.041	-.231	.817	-.091	.072	.000
Exchange Ideology	-.260	.060	-4.327	<.001	-.379	-.142	.066
[Scenario=1]	-.915	.201	-4.555	<.001	-1.311	-.520	.073
[Scenario=2]	-1.452	.202	-7.190	<.001	-1.849	-1.054	.164
[Scenario=3]	-1.915	.203	-9.438	<.001	-2.314	-1.515	.253
[Scenario=4]	0[a]	.	.	.	.	.	.
a. This parameter is set to zero because it is redundant.							

Our research findings indicate that any scenarios with bias have been viewed as less fair than the neutral scenario. Participants specifically identified the private-label bias as the most unfair among the three biased scenarios. In addition, the equity sensitivity and exchange ideology measurements in various contexts showed low deviation, indicating a consistent view across traits. The level of distrust towards recommendation systems was significantly lower in the neutral scenario compared to the biased scenarios. Within the several scenarios that demonstrated bias, the highest level of distrust was observed in the sponsored bias scenario, which highlighted major concerns over the impact of sponsorship on the integrity of recommendations (Table 21).

Table 21 Descriptive Statistics

Variable	Mean (SD)			
	Popularity Bias	Sponsored Bias	Private-Label Bias	Neutral
1. Perceived Fairness	3.68 (1.30)	3.18 (1.34)	2.64 (0.99)	4.64 (1.16)
2. Equity Sensitivity	5.64 (1.62)	5.72 (1.86)	5.78 (1.85)	5.26 (1.82)
3. Exchange Ideology	4.68 (1.23)	4.53 (1.35)	4.83 (1.25)	4.53 (1.36)
4. Distrust	4.58 (1.51)	4.95 (1.39)	4.84 (1.55)	3.37 (1.52)

Analyzing ANOVA results and Post Hoc tests presented in Table 22, Table 23 and Table 24, we observed substantial support for hypotheses H1a, H1b, and H1c. This confirmation of the hypotheses indicates that the underlying factors assessed in these tests significantly impact the variables under study, as evidenced by the statistical data.

Table 22 ANOVA Results

DV: Perceived Fairness	Sum of Squares	Df	Mean Square	F	Sig.
Between Groups	142.64	3.00	47.55	32.72	0.00
Within Groups	385.08	265.00	1.45		
Total	527.72	268.00			

Table 23 Post Hoc Test Multiple Comparison

Dependent Variable: Perceived Fairness							
Scenario			Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Tukey HSD	1	**2**	**0.50**	**0.21**	**0.08**	0.0	1.0

		3	1.04*	0.21	<.001	0.5	1.6
		4	-.96*	0.21	<.001	-1.5	-0.4
	2	1	-0.50	0.21	0.08	-1.0	0.0
		3	.54*	0.21	0.05	0.0	1.1
		4	-1.46*	0.21	<.001	-2.0	-0.9
	3	1	-1.04*	0.21	<.001	-1.6	-0.5
		2	-.54*	0.21	0.05	-1.1	0.0
		4	-2.00*	0.21	<.001	-2.5	-1.5
	4	1	.96*	0.21	<.001	0.4	1.5
		2	1.46*	0.21	<.001	0.9	2.0
		3	2.00*	0.21	<.001	1.5	2.5
Scheffe	1	2	0.50	0.21	0.12	-0.1	1.1
		3	1.04*	0.21	<.001	0.5	1.6
		4	-.96*	0.21	<.001	-1.5	-0.4
	2	1	-0.50	0.21	0.12	-1.1	0.1
		3	0.54	0.21	0.08	0.0	1.1
		4	-1.46*	0.21	<.001	-2.0	-0.9
	3	1	-1.04*	0.21	<.001	-1.6	-0.5
		2	-0.54	0.21	0.08	-1.1	0.0
		4	-2.00*	0.21	<.001	-2.6	-1.4
	4	1	.96*	0.21	<.001	0.4	1.5
		2	1.46*	0.21	<.001	0.9	2.0
		3	2.00*	0.21	<.001	1.4	2.6
Bonferroni	1	2	0.50	0.21	0.10	0.0	1.0
		3	1.04*	0.21	<.001	0.5	1.6
		4	-.96*	0.21	<.001	-1.5	-0.4
	2	1	-0.50	0.21	0.10	-1.0	0.0
		3	0.54	0.21	0.06	0.0	1.1
		4	-1.46*	0.21	<.001	-2.0	-0.9
	3	1	-1.04*	0.21	<.001	-1.6	-0.5
		2	-0.54	0.21	0.06	-1.1	0.0
		4	-2.00*	0.21	<.001	-2.6	-1.4
	4	1	.96*	0.21	<.001	0.4	1.5
		2	1.46*	0.21	<.001	0.9	2.0
		3	2.00*	0.21	<.001	1.4	2.6

*. The mean difference is significant at the 0.05 level.

Table 24 General Linear Model (Univariate) for Perceived Fairness

Tests of Between-Subjects Effects						
Dependent Variable: Perceived Fairness						
Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	142.645[a]	3	47.548	32.721	<.001	.270
Intercept	3358.314	1	3358.314	2311.087	<.001	.897
Scenario	142.645	3	47.548	32.721	<.001	.270
Error	385.080	265	1.453			
Total	3871.653	269				
Corrected Total	527.725	268				
R Squared = .270 (Adjusted R Squared = .262)						

In the regression model where distrust is the dependent variable, Table 25 shows that perceived fairness significantly lowers distrust. This is observed by a standardized coefficient (Beta) of -0.592, explaining 35% of the variance in distrust. In this study, hypothesis 4 posited that perceived fairness would inversely affect perceived distrust toward recommendation systems. The results from this study confirm this hypothesis, indicating that as perceived fairness increases, distrust decreases. This key finding highlights the importance of fairness in the design and operation of recommendation systems: perceived fairness significantly mitigates distrust among users. Thus, enhancing the fairness of these systems could be crucial in building user trust and improving the acceptance of system recommendations.

Table 25 Regression Results for Distrust

Dependent Variable: Distrust					
Model	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	t	Sig.
(Constant)	6.843	.215		31.833	<.001
Perceived Fairness	-.680	.057	-.592	-11.999	<.001

R-Square: 0.350; Adjusted R-Square: 0.348

In Table 26, a comprehensive overview of the hypotheses testing results is presented. The data confirms the majority of our hypotheses; however, Hypothesis H1d receives only partial support, and H2 is not supported. This table provides essential insights into the relationships and dynamics examined in our study, delineating areas where theoretical expectations align with empirical evidence and where discrepancies exist.

Table 26 Summary of Hypotheses Results

Hypothesis	Supported?
H1a: A customer who encounters popularity bias in a recommendation system will perceive it as less fair than a customer who does not encounter such bias	Yes
H1b: A customer who encounters sponsored bias in a recommendation system will perceive it as less fair than a customer who does not encounter such bias	Yes
H1c: A customer who encounters private-label bias in a recommendation system will perceive it as less fair than a customer who does not encounter such bias	Yes
H1d: A customer who encounters popularity bias in a recommendation system will perceive it as more fair than a customer who encounters sponsored or private label biases	Partially
H2: A customer with high equity sensitivity (entitled customer) will perceive recommendation systems as less fair than a customer with low equity sensitivity (benevolent customer)	No
H3: A customer with a high exchange ideology will perceive recommendation systems as less fair than a customer with low exchange ideology	Yes
H4: Perceived fairness will have a negative effect on perceived distrust	Yes

Chapter 6. Discussion

6.1 Interpretation of Results

This study provides insightful findings into the research questions it aimed to address. Addressing the first question, "*how do different biases in e-commerce recommendation systems impact the perceived fairness of such systems?*", the results indicate that recommendation systems exhibiting bias in favor of popular items, sponsored items, and private label products are generally perceived as less fair compared to neutral systems that do not exhibit these biases. These findings are consistent with, and build upon, the research conducted by Dash et al. (2021), Abdollahpouri et al. (2019) and Mansoury et al. (2019) highlighting the impact of various biases on perceived fairness.

The confirmation of hypothesis H1d highlights that customers perceive popularity bias as less unfair compared to sponsored and private-label biases. This study aligns with Edizel et al. (2019) which addressed algorithmic bias in recommendation systems, highlighting the significance of bias shaping individual's perception towards such systems. These findings are crucial for e-commerce companies, as they provide a deeper understanding of the various recommendation system biases and their differential impact on fairness perceptions. Our study builds upon the work of Wang et al. (2018) by demonstrating the effects of popularity, sponsored and private-label biases and demonstrates that customers regard biased recommendations for popular, sponsored, and private-label products in e-commerce systems as unfair. Among these biases, buyers find private-label product bias to be the most unfair, followed by sponsored and popularity biases. This enhances our understanding by identifying the varying degree to which different biases affect customer fairness perceptions.

Furthermore, recent research by Fang and Xu (2022), indicated that deviating from customer preferences in product recommendations can break the monotony of repetitive recommendations. While Dash et al. (2021) highlighted the bias in recommending popular products, our research suggests that e-commerce platforms can leverage this to enhance their recommendations by introducing serendipity and preventing information cocoons, ultimately benefiting the customers.

Transitioning to the second research question, "*how does customers' perceived fairness of recommendation systems impact their distrust toward e-commerce platforms?*", our study finds a negative relationship between perceived fairness and distrust in recommendation systems. This aligns with prior literature, like that of Wang et al. (2018) and sheds light on the mediating role of perceived fairness in the relationship between recommendation system bias and levels of distrust. Crucially, improving the perceived fairness of recommendation systems may play a vital role in mitigating distrust and fostering trust in e-commerce platforms (Benbasat and Wang, 2005). Additionally, it establishes a correlation between the perceived fairness of these recommendation systems and user distrust towards e-commerce platforms.

Lastly, addressing the third research question, "*how do customers' equity sensitivity and exchange ideology impact their perceived fairness of recommendation systems employed by e-commerce platforms?*" The study discovers that exchange ideology play significant role in explaining variations in perceived fairness, although the influence of equity sensitivity is not supported. Overall, this body of research enhances our comprehension of how equity sensitivity and exchange ideology impact individual responses to perceived fairness, offering significant implications for information systems and marketing strategies. Moreover, the study emphasizes that exchange ideology has a major influence on customers' perceptions of fairness in these systems.

The study finds that the biased recommendations of popular, sponsored and private label products in e-commerce recommendation systems lead to a perception of unfairness among customers. Among the biases studied, private-label product bias is perceived as the most unfair, followed by sponsored and popularity product bias. The study uncovers a negative relationship between the perceived fairness of recommendation systems and customers' distrust toward e-commerce platforms. Exchange Ideology is found to significantly influence perceptions of fairness in recommendation systems.

Our finding suggests that individuals find popularity, sponsored and private-label biases in recommendation systems as less fair compared to neutral recommendation systems. These findings empirically support the effect of algorithmic biases mentioned in the academic (Dash et al., 2019) and practitioner literature (FTC lawsuit). Further, we found the effect of herd behavior with respect to popularity bias as individuals find popularity bias to be relatively less unfair compared to private label bias.

IS and CS literature on algorithmic fairness assumes that fairness is objective and same for everyone; however, we found that exchange ideology, an individual trait, predicts the variation in perceived fairness. Although IS researchers have studied the link between perceived fairness and trust towards recommendation systems, we extend this literature by establishing the link between perceived fairness and distrust towards recommendation systems. Note that trust (Shin, 2021) is a different construct from distrust, and not its opposite. Furthermore, distrust (Wang et al., 2018) is a more appropriate construct in studying algorithmics biases.

6.2. Theoretical Contributions

This study makes several theoretical contributions by delving into the domain of AI fairness in recommendation systems used in e-commerce. Our research enriches the theoretical landscape of ethical AI by addressing the intricate issues of fairness within recommendation systems. Challenging the common belief that perceptions of recommendation systems are universally the same, our findings reveal a more complex reality. We find that personal traits, specifically exchange ideology, play a crucial role in shaping individuals' perceptions of fairness. Our results demonstrate that customers often view biased recommendation systems, such as those exhibiting sponsored, private-label, and popularity biases, as less fair than neutral ones.

A key finding of our study is the distinct impacts of different biases on fairness perception, shedding light on how users perceive these biases. Additionally, our research underscores exchange ideology's and equity sensitivity's influential roles in shaping fairness perceptions. This finding is particularly valuable, as it explains why individuals with a higher sense of entitlement may perceive these systems as less fair.

Furthermore, our study identifies a significant negative relationship between perceived fairness and distrust in recommendation systems. This highlights an important link between these variables, enhancing our understanding of how fairness perceptions influence customer attitudes and behaviors toward recommendation systems. Offering both theoretical and practical contributions, our study provides valuable insights into the nuances of fairness in recommendation systems, its driving factors, and its subsequent impact on user attitudes and behaviors in e-commerce.

This study enhances AI ethics and equity literature by demonstrating how personality traits, specifically exchange ideology, influence fairness perceptions in recommendation systems

(Scott & Colquitt, 2011). It also establishes a link between herd behavior and perception of algorithmic biases which explains how individuals perceive different types of biases (Sun, 2013; Feng, 2022). Additionally, we contribute to the literature on trust towards information systems by establishing that distrust as a significant outcome construct in the study of algorithmic biases (Shin, 2021).

6.3. Implications for Practice

The findings of this study provide valuable insights for industry practitioners, emphasizing the need to actively educate customers about AI-decision making processes and the various biases present in recommendation systems (Strich et al., 2021; Benbya et al., 2021; Pumplun et al., 2023). The findings are especially relevant for organizations seeking to enhance their recommendation systems, ensuring they better meet the diverse expectations and fair perceptions of their customers.

Additionally, recommendation system providers must adhere to Federal Trade Commission (FTC) regulations, guaranteeing the open disclosure of any sponsors and affiliated promotions. Establishing and maintaining customer trust in the neutrality of recommendation systems depends heavily on this approach. An extensive analysis of the literature in the field reveals a disconcerting pattern: many biased recommendation systems fail to reveal the sponsors' funding (Dast et al., 2021). When biases are apparent, transparent disclosure becomes vital for boosting customer trust. Customers may not become aware of biases initially, but with continued use, they may become more cognizant of them.

Understanding the influence of these biases on the perceived fairness of customers not only empowers them to make informed decisions but also guides policymakers and industry stakeholders in developing strategies to mitigate biases, ensuring a more fair and trustful online shopping experience for all users.

Algorithmics fairness is important to foster e-commerce customer trust towards recommendation systems. Segmenting customers by their fairness perception, such as exchange ideology, can guide e-commerce platforms in tailoring strategies across various customer touchpoints, lowering distrust towards such platforms.

6.4. Limitations

While this study has provided valuable insights, it is important to acknowledge its limitations. We acknowledge that our methodology, which relies on a survey-based experiment, may have limitations in external validity. Although vignette-based manipulation allows for control over experimental conditions, it may fall short of replicating the nuances of real-world user experiences. This limitation warrants careful consideration when applying our findings to actual usage scenarios. Furthermore, our use of self-reported measures to assess distrust could lead to the introduction of personal biases, potentially failing to capture the multifaceted nature of distrust as it unfolds in real-life contexts. This highlights the need for more sophisticated approaches in future research. For example, as suggested by Dimoka (2010), neurophysiological analysis could provide a more in-depth understanding of the fundamental aspects of distrust.

6.5. Implications for Future Research

This study lays the groundwork for a broader exploration of biases in recommendation systems and their impact on user perceptions and behaviors. While the current research employs a between-subjects design, it suggests that future studies should explore within-subjects designs and measure distrust of the customers at different time frames. We advocate for future research to extend beyond the scope of biases examined in this study, focusing on their influence on user interactions and the perception of fairness. A pivotal enhancement to future studies could involve the application of a recommendation system artifact, advancing beyond vignette-based treatments to augment the research model's validity. Further substantiation of our findings could be achieved through the analysis of secondary data from real-world recommendation platforms.

There exists a rich vein of inquiry into the effects of various biases—such as sponsored product bias, private-label bias, and popularity bias—on customer perceptions of fairness within AI-driven systems. An in-depth exploration of how these biases shape perceptions, influenced by factors like demographics, cultural contexts, and individual preferences, is warranted. Future research could dissect the psychological underpinnings of perceived unfairness associated with these biases, providing a multifaceted view of user engagement with recommendation systems.

Moreover, this study's between-subjects design paves the way for incorporating within-subjects designs in subsequent research, enabling a longitudinal analysis of shifts in user perceptions over time. A longitudinal perspective would also enrich our understanding of the dynamic interplay between distrust, fairness perceptions, and the continuous interaction with algorithmic recommendations. This insight is crucial for unraveling the temporal aspects of user engagement and the development of trust or distrust.

Looking ahead, the exploration of regulatory and policy implications related to biases in recommendation systems is of paramount importance, especially against the backdrop of growing antitrust concerns. Future research could evaluate the efficacy of current regulations, propose innovative regulatory frameworks, and delve into the role of transparency in bias mitigation. Such studies are essential for crafting guidelines that ensure fairness in recommendation systems.

Exploration of other types of biases and their impact on user perception and behavior. The future research can examine our research model using a recommendation system artifact instead of a vignette-based treatment. The findings of this study can be corroborated using secondary data from recommendation platforms.

In conclusion, this study serves as a launching pad for an extensive research agenda encompassing psychological, demographic, and regulatory dimensions of AI fairness in recommendation systems. Investigating these areas promises a comprehensive understanding of the factors influencing fairness perceptions and their impact on user behavior and attitudes.

6.6. Conclusion

This research paper provides important insights into the complex nature of e-commerce recommendation systems and their influence on the perception of fairness and customer distrust. It emphasizes the crucial aspect of neutrality in these systems, a topic that has garnered significant attention from academics, industry experts, and regulatory bodies.

Our research identifies a critical issue: biased recommendation systems in e-commerce can significantly erode customer trust, resulting in increased distrust. This highlights the pivotal role of customer perceptions towards these systems.

Moreover, the research examines how factors like equity sensitivity and exchange ideology shape fairness perceptions and, in turn, affect distrust in biased systems. From a practical perspective, this research offers valuable recommendations for industry practitioners. It outlines strategies for developing more effective recommendation systems that cater to the diverse needs of e-commerce customers. This involves acknowledging the subtle effects of various biases and the importance of transparency in the functioning of these systems.

References

Abdollahpouri, H., Mansoury, M., Burke, R., & Mobasher, B. (2019). The unfairness of popularity bias in recommendation. arXiv preprint arXiv:1907.13286.

Abdollahpouri, H., Mansoury, M., Burke, R., & Mobasher, B. (2020, September). The connection between popularity bias, calibration, and fairness in recommendation. In *Proceedings of the 14th ACM Conference on Recommender Systems* (pp. 726-731).

Adaji, I., & Vassileva, J. (2017). Perceived effectiveness, credibility and continuance intention in e-commerce: a study of Amazon. In *Persuasive Technology: Development and Implementation of Personalized Technologies to Change Attitudes and Behaviors: 12th International Conference, PERSUASIVE 2017, Amsterdam, The Netherlands, April 4–6, 2017, Proceedings 12* (pp. 293-306). Springer International Publishing.

Adam, J.S. (1963). Toward an understanding of inequity. *Journal of Abnormal and Social Psychology,* 67(5), 422-436.

Adams, J. S. (1965). Inequity in social exchange. In *Advances in experimental social psychology* (Vol. 2, pp. 267-299). Academic Press.

Adomavicius, G., Bockstedt, J. C., Curley, S. P., & Zhang, J. (2019). Reducing recommender system biases: An investigation of rating display designs. *MIS Quarterly*, *43*(4), 1321-1341.

Adomavicius, G., Bockstedt, J. C., Curley, S. P., & Zhang, J. (2018). Effects of online recommendations on consumers' willingness to pay. Information Systems Research, 29(1), 84-102.

Ahuja, S., Chan, Y. E., & Krishnamurthy, R. (2023). Responsible Innovation with Digital Platforms: Cases in India and Canada. Information Systems Journal, 33(1), 76-129. https://doi.org/10.1111/isj.12378

Anderson, J. C., & Gerbing, D. W. (1988). Structural equation modeling in practice: A review and recommended two-step approach. *Psychological bulletin*, 103(3), 411.

Animesh A, Viswanathan S, Agarwal R (2007) Online sponsored search advertising as a quality signal and its impact on consumer behavior. 28th Internat. Conf. Inform. Systems Proc., Montreal.

Aplin-Houtz, M. J., Leahy, S., Willey, S., Lane, E. K., Sharma, S., & Meriac, J. (2023). Tales from the dark side of technology acceptance: The Dark Triad and the Technology Acceptance Model. Employee Responsibilities and Rights Journal, 1-33.

Aplin-Houtz, M., Leahy, S., Willey, S., Lane, E., & Sharma, S. (2022). Tales from the Dark Side of Technology Acceptance: The Direct Effects of the Dark Triad on TAM. In Academy of Management Proceedings (Vol. 2022, No. 1, p. 11199). Briarcliff Manor, NY 10510: Academy of Management.

Avery, C., & Zemsky, P. (1998). Multidimensional uncertainty and herd behavior in financial markets. The American Economic Review, 88(4), 724–748.

Barber, B. The Logic and Limits of Trust. New Brunswick, NJ: Rutgers University Press, 1983.

Barclay D, Higgins C, Thompson R (1995) The partial least square (PLS) approach to causal modeling: personal computer adoption and use as an illustration. Tech. Stud. 2(2):285–309.

Barlow, Jordan B.; Warkentin, Merrill; Ormond, Dustin; and Dennis, Alan (2018) "Don't Even Think About It! The Effects of Antineutralization, Informational, and Normative

Communication on Information Security Compliance," Journal of the Association for Information Systems, 19(8), . Available at: https://aisel.aisnet.org/jais/vol19/iss8/3

Barocas, S., Hardt, M., & Narayanan, A. (2017). Fairness in machine learning. *Nips tutorial*, *1*, 2017.

Batmaz, Z., Yurekli, A., Bilge, A., & Kaleli, C. (2018). A review on deep learning for recommender systems: challenges and remedies. Artificial Intelligence Review, 52, 1-37. https://doi.org/10.1007/s10462-018-9654-y.

Benamati, J.S.; Sewa, M.A.; and Fuller, M.A. Are trust and distrust distinct constructs? An empirical study of the effects of trust and distrust among online banking users. In R.H. Sprague (ed.), Proceedings of the 39th Annual Hawaii International Conference on System Sciences. Los Alamitos, CA: IEEE Computer Society Press, 2006.

Benbasat, I.;, &Wang, W. (2005). Ttrust in and adoption of online recommendation agents. *Journal of the association for informations systems, 6(3),4.*

Benbya, H., Pachidi, S., & Jarvenpaa, S. (2021). Special issue editorial: Artificial intelligence in organizations: Implications for information systems research. Journal of the Association for Information Systems, 22(2), 10.

Bhattacherjee, A. (2001). An empirical analysis of the antecedents of electronic commerce service continuance. *Decision Support Systems*, 32(2), 201-214.

Binns, R. (2018, January). Fairness in machine learning: Lessons from political philosophy. In Conference on fairness, accountability and transparency (pp. 149-159). PMLR.

Binns, R. (2020, January). On the apparent conflict between individual and group fairness. In Proceedings of the 2020 conference on fairness, accountability, and transparency (pp. 514-524).

Blau, G., & Boal, K. (1989). Using job involvement and organizational commitment interactively to predict turnover. Journal of management, 15(1), 115-127.

Blau, P. M. (1964). Justice in social exchange. Sociological inquiry, 34(2), 193-206.

Bourdage, J. S., Goupal, A., Neilson, T., Lukacik, E. R., & Lee, N. (2018). Personality, equity sensitivity, and discretionary workplace behavior. *Personality and Individual Differences*, 120, 144-150.

Brewster, M (2022). E-Commerce Sales Surged During the Pandemic. US CENSUS BUREAU ECONOMIC INDICATORS. https://www.census.gov/economic-indicators/content/2022/20220217-ecommerce.html.

Bujold, A., Parent-Rocheleau, X., & Gaudet, M. C. (2022). Opacity behind the wheel: The relationship between transparency of algorithmic management, justice perception, and intention to quit among truck drivers. Computers in Human Behavior Reports, 8, 100245.

Cacioppo JT, Berntson G (1994) Relationship between attitudes and evaluative space: A critical review, with emphasis on the separability of positive and negative substrates. Psych. Bull. 115(3): 401–423.

Cacioppo JT, Gardner WL, Berntson GG (1997) Beyond bipolar conceptualizations and measures: The case of attitudes and evaluative space. Personality Soc. Psych. Rev. 1(1):3–25.

Cañamares, R., & Castells, P. (2018, June). Should I follow the crowd? A probabilistic analysis of the effectiveness of popularity in recommender systems. In *The 41st International ACM SIGIR Conference on Research & Development in Information Retrieval* (pp. 415-424).

Carr, C. L. (2007). The FAIRSERV model: Consumer reactions to services based on a multi-dimensional evaluation of service fairness. *Decision Sciences*, *38*(1), 107-130.

Çelen, B., & Kariv, S. (2004). Distinguishing informational cascades from herd behavior in the laboratory. American Economic Review, 94(3), 484–498.

Chau, D. C., Ngai, E. W., Gerow, J. E., & Thatcher, J. B. (2020). THE EFFECTS OF BUSINESS–IT STRATEGIC ALIGNMENT AND IT GOVERNANCE ON FIRM PERFORMANCE: A MODERATED POLYNOMIAL REGRESSION ANALYSIS. MIS quarterly, 44(4).

Chen, J., Dong, H., Wang, X., Feng, F., Wang, M., & He, X. (2020). Bias and Debias in Recommender System: A Survey and Future Directions. *ACM Transactions on Information Systems*. https://doi.org/10.1145/3564284.

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.

Chen, L., Hsieh, J. J., Rai, A., & Xu, S. (2021). How does employee infusion use of CRM systems drive customer satisfaction? Mechanism differences between face-to-face and virtual channels. *Liwei Chen, JJ Po-An Hsieh, and Arun Rai,'How does Intelligent System Empowerment Yield Payoff: Uncovering the Adaptive Mechanisms and the Contingency Role of Work Experience'Information Systems Research (A*),(Forthcoming), MIS Quarterly (45: 2)*, 719-754.

Cheng HK, Bandyopadhyay S, Guo H (2011) The debate on net neutrality: A policy perspective. Inform. Systems Res. 22(1):60–82

Cho, J. (2006). The mechanism of trust and distrust formation and their relational outcomes. Journal of retailing, 82(1), 25-35.

Ciampaglia, G. L., Nematzadeh, A., Menczer, F., & Flammini, A. (2018). How algorithmic popularity bias hinders or promotes quality. Scientific reports, 8(1), 15951.

Cipriani, M., & Guarino, A. (2014). Herd behavior in a laboratory financial market. American Economic Association, 95(5), 1427–1443.

Clement J. 2020. Annual net sales of Amazon 2004-2019. https://www.statista.com/statistics/266282/annual-net-revenue-of-amazoncom/. (2020).

Cohen, J. 1988. Statistical Power Analysis for Behavioral Sciences (2nd edition), Hillsdale, NJ: Lawrence Erlbaum Associates.

Colquitt , J . A .(2001) Dimensionality of organizational justice: Construct validation of a measure . *Journal of Applied Psychology* 86 (3) : 386 – 400

Connelly BL, Miller T, Devers CE (2012) Under a cloud of suspicion: Trust, distrust, and their interactive effect in interorganizational contracting. Strategic Management J. 33(7):820–833.

Cropanzano, R., & Mitchell, M. S. (2005). Social exchange theory: An interdisciplinary review. Journal of management, 31(6), 874-900.

D Mattioli, P Haggin, and S Shifflett. 2020. Amazon Restricts How Rival Device

Dash, Abhisek, Abhijnan Chakraborty, Saptarshi Ghosh, Animesh Mukherjee, and Krishna P. Gummadi. "When the umpire is also a player: Bias in private label product recommendations on e-commerce marketplaces." In *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency*, pp. 873–884. 2021.

Datta, P. (2011). A preliminary study of eCommerce adoption in developing countries. *Information systems journal*, 21(1), 3–32.

Davlembayeva, D., Papagiannidis, S., & Alamanos, E. (2021). Sharing economy platforms: An equity theory perspective on reciprocity and commitment. *Journal of Business Research*, 127, 151-166.

De Uster, Maria Valdivieso De Uster. 2018. "The 7 Biggest Trends Upending Sales Today." Available at https://www.salesforce.com/quotable/articles/biggest-sales-trends/, Accessed on 10/2/2018.

del Río-Lanza, A. B., Vázquez-Casielles, R., & Díaz-Martín, A. M. (2009). Satisfaction with service recovery: Perceived justice and emotional responses. *Journal of Business Research*, 62(8), 775-781.

Dellaert BGC, Häubl G (2012) Searching in choice mode: Consumer decision processes in product search with recommendations. J. Marketing Res. 49(2):277–288.

Deutsch, M. (1985). Distributive justice: A social-psychological perspective.

Diakopoulos, N. (2020). Accountability, Transparency, and Algorithms. The Oxford handbook of ethics of AI, 17(4), 197.

Dimoka A (2010) What does the brain tell us about trust and distrust? Evidence from a functional neuroimaging study. MIS Quart. 34(2):373–396.

Dirks K, Skarlicki D (2004) Trust in leaders: Existing research and emerging issues. Kramer R, Cook K, eds. Trust and Distrust in Organizations: Dilemmas and Approaches (Sage, Thousand Oaks, CA), 21–40.

Dirks, K. T., & Ferrin, D. L. (2002). Trust in leadership: meta-analytic findings and implications for research and practice. Journal of applied psychology, 87(4), 611.

Dou W, Lim K, Su C, Zhou N, Cui N (2010) Brand positioning strategy using search engine marketing. MIS Quart. 34(2):261–276.

Drehmann, M., Oechssler, J., & Roider, A. (2005). Herding and contrarian behavior in financial markets: an internet experiment. The American Economic Review, 95(5), 1403–1426.

Dwork, C., Hardt, M., Pitassi, T., Reingold, O., & Zemel, R. (2012, January). Fairness through awareness. In Proceedings of the 3rd innovations in theoretical computer science conference (pp. 214-226).

Dwork, C., Hardt, M., Pitassi, T., Reingold, O., & Zemel, R. (2012, January). Fairness through awareness. In Proceedings of the 3rd innovations in theoretical computer science conference (pp. 214-226).

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.

Edizel, B., Bonchi, F., Hajian, S., Panisson, A., & Tassa, T. (2019). FaiRecSys: mitigating algorithmic bias in recommender systems. *International Journal of Data Science and Analytics*, 1-17. https://doi.org/10.1007/s41060-019-00181-5.

Eisenberger, R., Huntington, R., Hutchison, S., & Sowa, D. (1986). Perceived organizational support. Journal of Applied psychology, 71(3), 500.

Erik Brynjolfsson, Yu Jeffrey Hu, and Michael D Smith. 2006. From niches to riches: Anatomy of the long tail. Sloan Management Review (2006), 67–71.

Fam, K. S., Richard, J. E., McNeill, L. S., Waller, D. S., & Zhang, H. (2022). Sales promotion: The role of equity sensitivity. *Asia Pacific Journal of Marketing and Logistics*, *34*(9), 1827-1848.

Fang, Shuyi and Xu, David (Jingjun), "Alleviating Information Cocoons and Fatigue with Serendipity: Effect of Relevant Diversification and its Timing" (2022). ICIS 2022 Proceedings. 16. https://aisel.aisnet.org/icis2022/hci_robot/hci_robot/16

Fang, Y., Qureshi, I., Sun, H., McCole, P., Ramsey, E., & Lim, K. H. (2014). Trust, satisfaction, and online repurchase intention. *Mis Quarterly*, *38*(2), 407-A9.

Fayyaz, Z., Ebrahimian, M., Nawara, D., Ibrahim, A., & Kashef, R. (2020). Recommendation systems: Algorithms, challenges, metrics, and business opportunities. applied sciences, 10(21), 7748.

Fehr, E., & Schmidt, K. M. (1999). A theory of fairness, competition, and cooperation. *The quarterly journal of economics*, 114(3), 817-868.

Fein S (1996) Effects of suspicion on attributional thinking and the correspondence bias. J. Personality Soc. Psych. 70(6):1164–1184.

Feng, Y. K., Claggett, J. L., Karahanna, E., & Tam, K. Y. (2022). A randomized field experiment to explore the impact of herding cues as catalysts for adoption. MIS Quarterly, 46(2).

Fenwick, M., McCahery, J. A., & Vermeulen, E. P. (2019). The end of 'corporate'governance: Hello 'platform'governance. European Business Organization Law Review, 20, 171-199.

Flavián, C., Gurrea, R., & Orús, C. (2020). Combining channels to make smart purchases: The role of webrooming and showrooming. Journal of Retailing and Consumer Services, 52, 101923.

Fleisher, W. (2021, July). What's fair about individual fairness?. In Proceedings of the 2021 AAAI/ACM Conference on AI, Ethics, and Society (pp. 480-490).

Fornell C, Larcker D (1981) Evaluating structural equation models with unobservable variables and measurement error. J. Marketing Res. 18(3):39–50

Fornell, C. (1992). A national consumer satisfaction barometer: The Swedish experience. *Journal of marketing*, 56(1), 6–21.

Federal Trade Commission. (2023). FTC Sues Amazon for Illegally Maintaining Monopoly power.

Garfinkle (2023). Amazon is quietly building the most powerful advertising machine in the world. Yahoo Finance. https://finance.yahoo.com/news/amazon-is-quietly-building-the-most-powerful-advertising-machine-in-the-world-135753395.html.

Ge, Y., Liu, S., Gao, R., Xian, Y., Li, Y., Zhao, X., ... & Zhang, Y. (2021, March). Towards long-term fairness in recommendation. In Proceedings of the 14th ACM international conference on web search and data mining (pp. 445-453)

George, D., & Mallery, P. (2019). *IBM SPSS statistics 26 step by step: A simple guide and reference*. Routledge.

Goel, S., Williams, K., & Dincelli, E. (2017). Got phished? Internet security and human

Goldberg, D., Nichols, D., Oki, B. M., & Terry, D. (1992). Using collaborative filtering to weave an information tapestry. *Communications of the ACM*, *35*(12), 61-70.

Gorgoglione, M., Panniello, U., & Tuzhilin, A. (2019). Recommendation strategies in personalization applications. Information & Management, 56(6), 103143.

Greenberg, J. (1990). Organizational justice: Yesterday, today, and tomorrow. *Journal of management*, *16*(2), 399–432.

Guijarro L, Pla V, Vidal JR, Martinez-Bauset J (2015) Search engine and content providers: Neutrality, competition and integration. Trans. Emerging Telecomm. Tech. 26(2):164–178.

Guo, Y., Wang, M., & Li, X. (2017). An interactive personalized recommendation system using the hybrid algorithm model. *Symmetry*, *9*(10), 216.

Gustafsson, A., Johnson, M. D., & Roos, I. (2005). The effects of consumer satisfaction, relationship commitment dimensions, and triggers on consumer retention. *Journal of marketing*, 69(4), 210-218.

H. Abdollahpouri, R. Burke, B. Mobasher, Controlling popularity bias in learning-to-rank recommendation, in: Proceedings of the Eleventh ACM Conference on Recommender Systems, 2017, pp. 42–46.

Hajian, S., Bonchi, F., & Castillo, C. (2016, August). Algorithmic bias: From discrimination discovery to fairness-aware data mining. In Proceedings of the 22nd ACM SIGKDD international conference on knowledge discovery and data mining (pp. 2125-2126).

Hardin R (2004) Distrust: Manifestations and management. Hardin R, ed. Distrust (Russell Sage Foundation, New York), 3–33.

Hardin, R. The street-level epistemology of trust. Politics and Society, 21, 4 (1993), 505–529

Harvey F (2003) Paid searches find the route to online riches: Internet: Advertisers' sponsorship of key words is becoming an important source of revenue for search engine providers. Financial Times (July 1), 14–14.

Herzog, S. (2003). The relationship between public perceptions of crime seriousness and support for plea-bargaining practices in Israel: A factorial survey approach. The Journal of Criminal Law & Criminology, 94(1), 103-131.

Ho, K. K., Au, C. H. A., & Chiu, D. K. (2021). Home Computer User Security Behavioral Intention: A Replication Study from Guam. *AIS Transactions on Replication Research*, *7*(1), 4Homburg, C., & Fürst, A. (2005). How organizational complaint handling drives customer loyalty: an analysis of the mechanistic and the organic approach. *Journal of Marketing*, 69(3), 95-114.

Homans, G. C. (1958). Social behavior as exchange. American journal of sociology, 63(6), 597-606.

Hosanagar, K., Fleder, D., Lee, D., & Buja, A. (2014). Will the global village fracture into tribes? Recommender systems and their effects on consumer fragmentation. *Management Science*, *60*(4), 805–823.

Houpt, J., Blaha, L., McIntire, J., Havig, P., & Townsend, J. (2014). Systems factorial technology with R. Behavior Research Methods, 46, 307-330. https://doi.org/10.3758/s13428-013-0377-3.

Hoyle, R. H. (Ed.). (1999). *Statistical strategies for small sample research*. sage.

Hoyle, R. H., & Kenny, D. A. (1999). Sample size, reliability, and tests of statistical mediation. *Statistical strategies for small sample research*, 1, 195–222.

Hsieh, J. J. P.-A., Rai, A., & Keil, M. (2008). Understanding digital inequality: comparing continued use behavioral models of the socio-economically advantaged and disadvantaged. MIS Quarterly, 32(1), 97–126.

Huseman, R. C., Hatfield, J. D., & Miles, E. W. (1987). A new perspective on equity theory: The equity sensitivity construct. *Academy of Management Review*, 12, 222–234.

Ishida, Y., Uchiya, T., & Takumi, I. (2017). Design and evaluation of a movie recommendation system showing a review for evoking interested. *International Journal of Web Information Systems*, *13*(1), 72-84.

Jackson, D. L. (2003). Revisiting sample size and number of parameter estimates: Some support for the N: q hypothesis. *Structural equation modeling*, *10*(1), 128–141.

Jannach, D., Lerche, L., Kamehkhosh, I., & Jugovac, M. (2015). What recommenders recommend: an analysis of recommendation biases and possible countermeasures. *User Modeling and User-Adapted Interaction*, *25*, 427-491.

Jasso, G. (2006). Factorial survey methods for studying beliefs and judgments. Sociological Methods & Research, 34(3), 334-423.

Johnson, M. D., & Fornell, C. (1991). A framework for comparing consumer satisfaction across individuals and product categories. Journal of economic psychology, 12(2), 267-286.

Johnston, A. C., Warkentin, M., McBride, M. E., & Carter, L. (2016). Dispositional and situational factors: Influences in IS security policy violations. European Journal of Information Systems, 25(3), 231-251.

Kahneman D, Tversky (1979) A prospect theory: An analysis of decisions under risk. Econometrica 47:263–291.

Kane, G. C., Young, A. G., Majchrzak, A., & Ransbotham, S. (2021). Avoiding an oppressive future of machine learning: A design theory for emancipatory assistants. MIS Quarterly, 45(1), 371-396.

Karahanna, E., & Straub, D. W. (1999). The psychological origins of perceived usefulness and ease-of-use. Information & Management, 35(4), 237–250

Karren, R., & Barringer, M. (2002). A Review and Analysis of the Policy-Capturing Methodology in Organizational Research: Guidelines for Research and Practice. Organizational Research Methods, 5, 337 - 361. https://doi.org/10.1177/109442802237115.

Katona Z, Sarvary M (2010) The race for sponsored links: Bidding patterns for search advertising. Marketing Sci. 29(2):199–215.

Kickul, J., & Lester, S. W. (2001). Broken promises: Equity sensitivity as a moderator between psychological contract breach and employee attitudes and behavior. *Journal of Business and Psychology*, 16, 191-217.

King Jr, W. C., & Miles, E. W. (1994). The measurement of equity sensitivity. *Journal of Occupational and Organizational Psychology*, 67(2), 133–142.

King Jr, W. C., Miles, E. W., & Day, D. D. (1993). A test and refinement of the equity sensitivity construct. Journal of Organizational Behavior, 14(4), 301-317.

King, W. R., & He, J. (2006). A meta-analysis of the technology acceptance model. Information&Management, 43(6), 740–755.

Kizilcec, R. F. (2016, May). How much information? Effects of transparency on trust in an algorithmic interface. In *Proceedings of the 2016 CHI conference on human factors in computing systems* (pp. 2390-2395).

Kline, R. B. (1998). Structural equation modeling. *New York: Guilford*.

Kline, R. B. (2015). *Principles and practice of structural equation modeling*. Guilford publications.

Kohan, S. (2020). Purchasing on mobile devices will drive holiday sales and hit $314 billion this year. Forbes. https://www.forbes.com/sites/shelleykohan/2020/09/22/purchasing-on-mobile-devices-will-drive-holiday-sales-and-hit-314-billion-this-year/?sh=6b1df8f7d761

Komiak SYX, Benbasat I (2008) A two-process view of trust and distrust building in recommendation agents: A process-tracing study. J. Assoc. Inform. Systems 9(12):727–747.

Kramer J, Wiewiorra L, Weinhardt C (2013) Net neutrality: A progress ¨report. Telecomm. Policy 37(9):794–813.

Kramer RM, Brewer MB, Hanna BA (1996) Collective trust and collective action: The decision to trust as a social decision. Kramer RM, Tyler TR, eds. Trust in Organizations: Frontiers of Theory and Research (Sage, Thousand Oaks, CA), 357–389.

Kreitchmann, R. S., Abad, F. J., Ponsoda, V., Nieto, M. D., & Morillo, D. (2019). Controlling for response biases in self-report scales: Forced-choice vs. psychometric modeling of Likert items. Frontiers in psychology, 10, 2309.

Krishnan, P. (2020). When and how to use factorial design in nursing research. *Nurse researcher*. https://doi.org/10.7748/nr.2020.e1757.

Krishnasamy S, Sen R, Oh S, Shakkottai S (2015) Detecting sponsored recommendations. ACM SIGMETRICS Performance Evaluation Rev. 43(1):445–446.

Kung, F., Kwok, N., & Brown, D. (2018). Are Attention Check Questions a Threat to Scale Validity?. *Applied Psychology*, 67, 264–283. https://doi.org/10.1111/apps.12108.

Labeaga, J. M., Lado, N., & Martos, M. (2007). Behavioural loyalty towards store brands. *Journal of Retailing and consumer services*, 14(5), 347-356.

Le Bon, G. (2002). The crowd: A study of the popular mind. Courier Corporation.

Le Chen, Ruijun Ma, Anikó Hannák, and Christo Wilson. [n.d.]. *In Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*

Leahy, S., Aplin-Houtz, M. J., Willey, S., Lane, E. K., Sharma, S., & Meriac, J. (2023). The Light Side of Technology Acceptance: The Direct Effects of the Light Triad on the Technology Acceptance Model 1. Journal of Managerial Issues, 35(3), 300-330.

Lebow, S. (2021). Worldwide ecommerce continues double-digit growth following pandemic push to online. *eMarketer, 19th August, available at: https://www. emarketer. com/content/worldwide-ecommerce-continues-double-digit-growth-following-pandemic-push-online (accessed 21st January, 2022)*.

Lee, J., Lee, J. N., & Tan, B. C. (2015). Antecedents of cognitive trust and affective distrust and their mediating roles in building customer loyalty. Information Systems Frontiers, 17, 159-175.

Lee, K., Joshi, K., & Kim, Y. K. (2011). Identification of the four-factor structure of consumers' perceived fairness. *Journal of Targeting, Measurement and Analysis for Marketing*, 19(2), 113-126.

Lee, S. S., Vollmer, B. T., Yue, C. A., & Johnson, B. K. (2021). Impartial endorsements: Influencer and celebrity declarations of non-sponsorship and honesty. Computers in Human Behavior, 122, 106858.

Lewicki RJ, Mcallister DJ, Bies RJ (1998) Trust and distrust: New relationships and realities. Acad. Management Rev. 23(3):438–458

Lewicki, R. J., & Bunker, B. B. (1996). Developing and maintaining trust in work relationships. Trust in organizations: Frontiers of theory and research, 114(139), 30.

Lewicki, R.J., McAllister, D.J., and Bies, R.J. Trust and distrust: New relationships and realities. Academy of Management Review, 23, 3 (1998), 438–458

Li, C. T., Hsu, C., & Zhang, Y. (2022). Fairsr: Fairness-aware sequential recommendation through multi-task learning with preference graph embeddings. ACM Transactions on Intelligent Systems and Technology (TIST), 13(1), 1-21.

Li, L., Chen, J., & Raghunathan, S. (2020). Informative Role of Recommender Systems in Electronic Marketplaces: A Boon or a Bane for Competing Sellers. *MIS Quarterly*, 44(4).

Li, S., & Karahanna, E. (2015). Online Recommendation Systems in a B2C E-Commerce Context: A Review and Future Directions. *J. Assoc. Inf. Syst.*, 16, 2. https://doi.org/10.17705/1jais.00389.

Li, Y., Chen, H., Fu, Z., Ge, Y., & Zhang, Y. (2021, April). User-oriented fairness in recommendation. *In Proceedings of the Web Conference* 2021 (pp. 624-632).

Liang, C. C., Liang, W. Y., & Tseng, T. L. (2019). Evaluation of intelligent agents in consumer-to-business e-Commerce. *Computer Standards & Interfaces*, *65*, 122-131

Lin, H. H., & Wang, Y. S. (2006). An examination of the determinants of consumer loyalty in mobile commerce contexts. *Information & management*, 43(3), 271-282.

Lina M Khan. 2016. Amazon's antitrust paradox. Yale LJ (2016)

Lowry, P. B., Xiao, J., & Yuan, J. (2023). How Lending Experience and Borrower Credit Influence Rational Herding Behavior in Peer-to-Peer Microloan Platform Markets. *Paul Benjamin Lowry, Junji Xiao, and* Jia Yuan (2023).“How lending experience and borrower credit influence rational herding behavior in peer-to-peer microloan platform markets,” Journal of Management Information Systems (JMIS)(accepted 07-Mar-20.*

Luhmann N (1979) Trust and Power (Wiley, New York).

Mackay, C. (1841). Extraordinary Popular Delusions and the Madness of Crowds, reprint. New York: Noonday.

MacMillan, N. A. (2002). Signal detection theory. In Stevens' Handbook of Experimental Psychology, American Cancer Society.

Makers Buy Ads on Its Site. https://www.wsj.com/articles/amazon-restricts advertising-competitor-device-makers-roku-arlo-11600786638. (Sep 2020).

Douglas, B. D., Ewell, P. J., & Brauer, M. (2023). Data quality in online human-subjects research: Comparisons between MTurk, Prolific, CloudResearch, Qualtrics, and SONA. Plos one, 18(3), e0279720.

Eyal, P., David, R., Andrew, G., Zak, E., & Ekaterina, D. (2021). Data quality of platforms and panels for online behavioral research. Behavior research methods, 1-20.

Palan, S., & Schitter, C. (2018). Prolific. ac—A subject pool for online experiments. Journal of Behavioral and Experimental Finance, 17, 22-27.

Joshi, A., Kale, S., Chandel, S., & Pal, D. K. (2015). Likert scale: Explored and explained. British journal of applied science & technology, 7(4), 396-403.

Malgonde, O. S., Zhang, H., Padmanabhan, B., & Limayem, M. (2022). Managing Digital Platforms with Robust Multi-Sided Recommender Systems. *Journal of Management Information Systems*, *39*(4), 938-968.

Malgonde, O., Zhang, H., Padmanabhan, B., & Limayem, M. (2020). TAMING COMPLEXITY IN SEARCH MATCHING: TWO-SIDED RECOMMENDER SYSTEMS ON DIGITAL PLATFORMS. *Mis Quarterly*, *44*(1).

Mansoury, M., Mobasher, B., Burke, R., & Pechenizkiy, M. (2019). Bias disparity in collaborative recommendation: Algorithmic evaluation and comparison. *arXiv preprint arXiv:1908.00831*.

Masuch, K., Hengstler, S., Trang, S., & Brendel, A. B. (2020). Replication Research of Moody, Siponen, and Pahnila's Unified Model of Information Security Policy Compliance. *AIS Transactions on Replication Research*, *6*(1), 13.

Mattila , A . S .and Cranage , D .(2005) The impact of choice on fairness in the context of service recovery . *The Journal of Services Marketing* 19 (5) : 271 – 279.

Maxham III, J. G., & Netemeyer, R. G. (2003). Firms reap what they sow: the effects of shared values and perceived organizational justice on customers' evaluations of complaint handling. *Journal of Marketing*, 67(1), 46-62.

Mayer, R. C., & Gavin, M. B. (2005). Trust in management and performance: Who minds the shop while the employees watch the boss?. Academy of management journal, 48(5), 874-888.

Mayer, R. C., Davis, J. H., & Schoorman, F. D. (1995). An integrative model of organizational trust. Academy of management review, 20(3), 709-734.

McCabe et al. (2023, 10 25) What the U.S. Has Argued in the Google Antitrust Trial. The New York Times.

McKnight, D. H., Choudhury, V., & Kacmar, C. (2002). Developing and validating trust measures for e-commerce: An integrative typology. Information systems research, 13(3), 334-359.

Miller, B. K., & Simmering, M. J. (2022). Attitude toward the color blue: An ideal marker variable. *Organizational Research Methods*, 10944281221075361.

Miller, B. K., & Simmering, M. J. (2023). Attitude toward the color blue: An ideal marker variable. Organizational Research Methods, 26(3), 409-440.

Moody, G. D., Galletta, D. F., & Lowry, P. B. (2014). When trust and distrust collide online: The engenderment and role of consumer ambivalence in online consumer behavior. Electronic Commerce Research and Applications, 13(4), 266-282.

Mukherjee, D., Yurochkin, M., Banerjee, M., & Sun, Y. (2020, November). Two simple ways to learn individual fairness metrics from data. In International Conference on Machine Learning (pp. 7097-7107). PMLR.

Neal, R. (2007). Pattern Recognition and Machine Learning. Technometrics, 49, 366 - 366. https://doi.org/10.1198/tech.2007.s518.

Niehoff B, Paul R (2001) The just workplace: Developing and maintaining effective psychological contracts. Bus. Rev. 22(1):5–8

Nunnally JC, Bernstein IH (1994) Psychometric Theory (McGraw-Hill, New York)

O'Fallon, M. & Butterfield, K. (2005). A review of the empirical ethical decision-making literature: 1996-2003. Journal of Business Ethics, 59(4), 375-413.

Oppenheimer, D. M., Meyvis, T., & Davidenko, N. (2009). Instructional manipulation checks: Detecting satisficing to increase statistical power. Journal of Experimental Social Psychology, 45(4), 867-872.

Òscar Celma and Pedro Cano. 2008. From hits to niches?: or how popular artists can bias music recommendation and discovery. In Proceedings of the 2nd KDD Workshop on Large-Scale Recommender Systems and the Netflix Prize Competition. ACM, 5

Ou CX, Sia CL (2010) Consumer trust and distrust: An issue of website design. Internat. J. Human-Comput. Stud. 68(12):913–934.

Paas, L., Dolnicar, S., & Karlsson, L. (2018). Instructional Manipulation Checks: A longitudinal analysis with implications for MTurk. International Journal of Research in Marketing. https://doi.org/10.1016/J.IJRESMAR.2018.01.003.

Patel (2023, 10 16) The Google antitrust trial has been frustratingly locked down — the NYT just filed a motion to open it up. The Verge.

Pathak, B., Garfinkel, R., Gopal, R. D., Venkatesan, R., & Yin, F. (2010). Empirical analysis of the impact of recommender systems on sales. Journal of Management Information Systems, 27(2), 159-188.

Patro, G. K., Biswas, A., Ganguly, N., Gummadi, K. P., & Chakraborty, A. (2020, April). Fairrec: Two-sided fairness for personalized recommendations in two-sided platforms. In *Proceedings of the web conference 2020* (pp. 1194-1204).

Pavlou PA, Gefen D (2005) Psychological contract violation in online marketplaces: Antecedents, consequences, and moderating role. Inform. Systems Res. 16(4):372–399.

Pavlou PA, Liang H, Xue Y (2007) Understanding and mitigating uncertainty in online exchange relationships: A principal-agent perspective. MIS Quart. 31(1):105–136.

Peng, Jing and Liang, Chen. 2023. "On the Differences Between View-Based and Purchase-Based Recommender Systems," *MIS Quarterly*, (47: 2) pp.875-900.

Perugini, S., Gonçalves, M., & Fox, E. (2004). Recommender Systems Research: A Connection-Centric Survey. Journal of Intelligent Information Systems, 23, 107-143. https://doi.org/10.1023/B:JIIS.0000039532.05533.99.

Podsakoff, P., MacKenzie, S., Lee, J., & Podsakoff, N. (2003). Common method biases in behavioral research: a critical review of the literature and recommended remedies.. *The*

Journal of applied psychology, 88 5, 879-903 . https://doi.org/10.1037/0021-9010.88.5.879.

Politicio Staff (2023, 09 23). Read the FTC's lawsuit against Amazon. Politico.

Press Information Bureau. 2018. Review of policy on Foreign Direct Investment (FDI) in e-commerce. http://www.pib.nic.in/PressReleseDetail.aspx?PRID=1557380. (2018)

PricewaterhouseCoopers (2017) IAB internet advertising revenue report. Report, IAB and PricewaterhouseCoopers, New York.

Protasiewicz, J., Pedrycz, W., Kozłowski, M., Dadas, S., Stanislawek, T., Kopacz, A., & Galezewska, M. (2016). A recommender system of reviewers and experts in reviewing problems. Knowl. Based Syst., 106, 164-178. https://doi.org/10.1016/j.knosys.2016.05.041.

Pumplun, L., Peters, F., Gawlitza, J. F., & Buxmann, P. (2023). Bringing Machine Learning Systems into Clinical Practice: A Design Science Approach to Explainable Machine Learning-Based Clinical Decision Support Systems. Journal of the Association for Information Systems, 24(4), 953-979.

Ransom D (2010) Seven ways to make pay-per-click pay. Wall Street Journal (March 2), http://online.wsj.com/article/SB10001424052748704548604575098011190760930.html.

Robinson SL (1996) Trust and breach of the psychological contract. Admin. Sci. Quart. 41(4):574–599.

Rousseau, D.M.; Sitkin, S.B.; Burt, R.S.; and Camerer, C. Not so different after all: A cross-discipline view of trust. Academy of Management Review, 23, 3 (1998), 393–404

Schepers, J., & Wetzels, M. (2007). A meta-analysis of the technology acceptance model: Investigating subjective norm and moderation effects. Information & Management, 44(1), 90–103.

Scott, B. A., & Colquitt, J. A. (2007). Are organizational justice effects bounded by individual differences? An examination of equity sensitivity, exchange ideology, and the Big Five. *Group & Organization Management*, *32*(3), 290-325.

Seron, C., Pereira, J., & Kovath, J. (2006). How citizens assess just punishment for police misconduct. Criminology, 44(4), 925-960.

Settoon, R. P., & Mossholder, K. W. (2002). Relationship quality and relationship context as antecedents of person-and task-focused interpersonal citizenship behavior. Journal of applied psychology, 87(2), 255.

Shalini Chandra, Anuragini Shirish & Shirish C. Srivastava (2022) To Be or Not to Be …Human? Theorizing the Role of Human-Like Competencies in Conversational Artificial Intelligence Agents, Journal of Management Information Systems, 39:4, 969-1005, DOI: 10.1080/07421222.2022.2127441

Shani, G., & Gunawardana, A. (2011). Evaluating recommendation systems. *Recommender systems handbook*, 257-297.

Shankar Prawesh, Balaji Padmanabhan (2014) The "Most Popular News" Recommender: Count Amplification and Manipulation Resistance. Information Systems Research 25(3):569-589.

Sharma, S., Singh, V. K., & Joshi, K. (2023). Fairness of E-Commerce Platform Product Recommendations: Understanding Customers' Perceived Fairness and Equity Sensitivity.

Shin, D. (2020). User perceptions of algorithmic decisions in the personalized AI system: perceptual evaluation of fairness, accountability, transparency, and explainability. *Journal of Broadcasting & Electronic Media*, *64*(4), 541–565.

Shin, D. (2021). The effects of explainability and causability on perception, trust, and acceptance: Implications for explainable AI. *International Journal of Human-Computer Studies*, p. 146, 102551.

Shin, D., & Park, Y. J. (2019). Role of fairness, accountability, and transparency in algorithmic affordance. *Computers in Human Behavior*, *pp. 98*, 277-284.

Smith, J., Sonboli, N., Fiesler, C., & Burke, R. (2020). Exploring user opinions of fairness in recommender systems. *arXiv preprint arXiv:2003.06461*.

Smith, S. M., Roster, C. A., Golden, L. L., & Albaum, G. S. (2016). A multi-group analysis of online survey respondent data quality: Comparing a regular USA consumer panel to MTurk samples. *Journal of Business Research*, *69*(8), 3139-3148.

Song J, Jones D, Gudigantala N (2007) The effects of incorporating compensatory choice strategies in web-based consumer decision support systems. Decision Support Systems 43(2):359–374.

Soper, D.S. (2023). A-priori Sample Size Calculator for Structural Equation Models [Software]. Available from https://www.danielsoper.com/statcalc

Stevens, J. P. (2009). Applied multivariate statistics for the social sciences (5th ed). New York, NY: Taylor & Francis.

Strich, F., Mayer, A. S., & Fiedler, M. (2021). What do I do in a world of artificial intelligence? Investigating the impact of substitutive decision-making AI systems on employees' professional role identity. Journal of the Association for Information Systems, 22(2), 9.

Tabachnick, B. G., & Fidell, L. S. (2001). Using Multivariate Statistics, Allyn and Bacon, Boston, MA. *Using Multivariate Statistics, 4th ed. Allyn and Bacon, Boston, MA.*

Tam, K. Y., and Ho, S. Y. (2006). "Understanding the Impact of Web Personalization on User Information Processing and Decision Outcomes, *MIS Quarterly* (30:4), pp. 865–890.

Tan, J., Tyler, K., & Manica, A. (2007). Business-to-business adoption of eCommerce in China. *Information & Management*, 44(3), 332–351.

Tax, S. S., Brown, S. W., & Chandrashekaran, M. (1998). Customer evaluations of service complaint experiences: implications for relationship marketing. *Journal of Marketing*, 62(2), 60-76.

Terlizzi, M. A., Brandimarte, L., & Sanchez, O. (2019). Replication of Internet privacy concerns in the mobile banking context. *AIS Transactions on Replication Research*, *5*(1), 8.

Thaw, Y. Y., Mahmood, A. K., & Dominic, P. (2009). A Study on the factors that influence the consumers trust on ecommerce adoption. *arXiv preprint arXiv:0909.1145*.

Thibaut, J. W., & Walker, L. (1975). *Procedural justice: A psychological analysis*. L. Erlbaum Associates.

This ranking by the recommendation algorithms may not align with customer expectations, potentially leading to distrust.

Tinsley, H. E., & Tinsley, D. J. (1987). Uses of factor analysis in counseling psychology research. *Journal of counseling psychology*, 34(4), 414.

Tran, T. N. T., Felfernig, A., Trattner, C., & Holzinger, A. (2021). Recommender systems in the healthcare domain: state-of-the-art and research issues. *Journal of Intelligent Information Systems*, 57(1), 171-201.

Trinkle, B. S., Crossler, R. E., & Warkentin, M. (2014). I'm game, are you? Reducing realworld security threats by managing employee activity in virtual environments. Journal of Information Systems, 28(2), 307-327.

Trotter, W. (1921). Instincts of the Herd in Peace and War. TF Unwin Limited.

Vance, A., Eargle, D., Eggett, D., Straub, D., & Ouimet, K. (2022). Do security fear appeals work when they interrupt tasks? A multi-method examination of password strength.

Vassilakopoulou, P., Parmiggiani, E., Shollo, A., & Grisot, M. (2022). Responsible AI: Concepts, critical perspectives and an Information Systems research agenda. *Scandinavian Journal of Information Systems*, *34*(2), 3.

Wallander, L. (2009). 25 years of factorial surveys in sociology: A review. Social Science Research, 38(3), 505-520

Alamdari, P. M., Navimipour, N. J., Hosseinzadeh, M., Safaei, A. A., & Darwesh, A. (2020). A systematic study on the recommender systems in the E-commerce. Ieee Access, 8, 115694-115716.

Wang W, Benbasat I (2013) A contingency approach to investigating the effects of user-system interaction modes of online decision aids. Inform. Systems Res. 24(3):861–876.

Wang W, Xu JD, 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 Sci. 64(11): 5198–5219.

Wang, W., & Wang, M. (2019). Effects of sponsorship disclosure on perceived integrity of biased recommendation agents: Psychological contract violation and knowledge-based trust perspectives. Information Systems Research, 30(2), 507-522.

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), 1-43.

Wedel, Michel and P. K. Kannan. 2016. "Marketing Analytics for Data-Rich Environments." *Journal of Marketing* 80 (6): 97-121.

Wei, T., Feng, F., Chen, J., Wu, Z., Yi, J., & He, X. (2021, August). Model-agnostic counterfactual reasoning for eliminating popularity bias in recommender system. In Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery & Data Mining (pp. 1791-1800).

Weiquan Wang, J. Xu, and M. Wang (November 2018), "Effects of Recommendation Neutrality and Sponsorship Disclosure on Trust versus Distrust in Online Recommendation Agents: Moderating Role of Explanations for Organic Recommendations," Management Science, 64(11), 5198-5219.

Wheeler, K. G. (2002). Cultural values in relation to equity sensitivity within and across cultures. *Journal of Managerial Psychology*, *17*(7), 612-627.

White, A., & Bodoni, S. (2020, November). Amazon is turning advertising into its next huge business– here's how. Bloomberg. https://www.bloomberg.com/news/articles/2020-11-10/amazon-set-to-get-eu-antitrust-objections-over-sales-data.

Willison, R., Warkentin, M., & Johnston, A. C. (2018) Examining employee computer abuse intentions: Insights from justice, deterrence and neutralization perspectives. Information Systems Journal, 28(2), 266-293.

Winder D (2011) Can you trust Google sponsored results? PC Pro.

Witt, L. A., & Broach, D. (1993). Exchange ideology as a moderator of the procedural justice-satisfaction relationship. The Journal of social psychology, 133(1), 97-103.

Witt, U. (1992). Evolutionary concepts in economics. Eastern Economic Journal, 18(4), 405-419.

Xiang (Shawn) Wan, Anuj Kumar, Xitong Li (2023) Retargeted Versus Generic Product Recommendations: When is it Valuable to Present Retargeted Recommendations? Information Systems Research 0(0). https://doi.org/10.1287/isre.2020.0560

Xiao B, Benbasat I (2011) Product-related deception in e-commerce: A theoretical perspective. MIS Quart. 35(1):169–196.

Yang S, Ghose A (2010) Analyzing the relationship between organic and sponsored search advertising: Positive, negative, or zero interdependence? Management Sci. 29(4):602–623.

Ye, H., & Kankanhalli, A. (2018). User Service Innovation on Mobile Phone Platforms. MIS quarterly, 42(1), 165-A9.

Yoon-Joo Park and Alexander Tuzhilin. 2008. The long tail of recommender systems and how to leverage it. In Proceedings of the 2008 ACM conference on Recommender systems. ACM, 11–18.

Zhang, J. (2011). The perils of behavior-based personalization. *Marketing Science*, 30(1), 170-186.

Zhang, Y., Feng, F., He, X., Wei, T., Song, C., Ling, G., & Zhang, Y. (2021, July). Causal intervention for leveraging popularity bias in recommendation. In Proceedings of the 44th International ACM SIGIR Conference on Research and Development in Information Retrieval (pp. 11-20).

Zhang, Q., Lu, J., & Jin, Y. (2021). Artificial intelligence in recommender systems. Complex & Intelligent Systems, 7(1), 439-457.

Appendix A: IRB Approval

UMSL eCompliance

IRB #2096605 SL

/ IRB / My IRB Projects / IRB #2096605 SL / IRB Application: 392333 / Print form

Project number	2096605
Principal investigator	Sharma, Sachin (UMSL-Student)
Project title	(Un)Fair E-Commerce Recommendations? Understanding Perceived Recommendation Fairness, Equity Sensitivity, Customer Satisfaction, and Loyalty on E-commerce Platforms.
Project status	Active - Exempt
App. status	Approved
App. approved	07/03/2023
Expiration date	07/03/2024

IRB #2096605 SL

IRB Application #392333

Submission date: **06/22/2023**
Submitted by: **Sharma, Sachin (UMSL-Student)**

1. Project Title/Investigators

1. **Project Title**

   If the study is externally funded or internally grant funded, this title should match the title on the grant/contract.

   (Un)Fair E-Commerce Recommendations? Understanding Perceived Recommendation Fairness, Equity Sensitivity, Customer Satisfaction, and Loyalty on E-commerce Platforms.

2. ***Key Personnel - List all investigators engaged in the research by clicking on the "Add an Investigator" button.*** *This includes individuals interacting or intervening with subjects, collecting or accessing identifiable data, or consenting subjects. Please note, if individuals are performing services that are typically performed for non-research purposes, and they are only providing a service for this project, they do not need to be listed.*

   Principal Investigator Assurance*: After you hit submit on this application, the PI will be sent an email from the system requesting the completion of the PI Assurance Form. This application will not officially be submitted to the IRB until this step is complete.*

   Primary Contact(s)*: Whoever you would like to be copied on IRB correspondence, including reminders and approvals, please be sure to add them as primary contacts when prompted under the "Add an Investigator" button. There must be at least one primary contact on this application.*

Appendix B: Consent Form

University of Missouri–St. Louis
Informed Consent for Participation in Research Activities

Project Title: (Un)Fair E-Commerce Recommendations? Understanding Perceived Recommendation Fairness, Equity Sensitivity, Customer Satisfaction, and Distrust on E-commerce Platforms
Principal Investigator: Sachin Sharma
Department Name: Doctor of Business Administration Program
Faculty Advisor: Dr. Vivek K. Singh
IRB Project Number: 2096605 SL

1. You are invited to participate in a research study to understand individuals' perceptions of e-commerce recommendations and platforms. You will be asked to complete an online survey on the Qualtrics website.
2. You will participate once in this survey. The survey includes questions about your perception of fairness toward e-commerce recommendations, equity sensitivity, and demographics. Additionally, you will be asked questions related to distrust, and consumer satisfaction toward e-commerce platforms. This survey should take approximately 15-20 minutes of your time.
3. There are no known risks and discomforts if you take part in this research study except for the potential for mild boredom and fatigue. You will be compensated for taking part in this study.
4. For your time and effort, we will pay a fixed compensation of $4.00 for the completion of the entire survey. A fixed partial compensation of $2.00 will be paid for incomplete surveys. Participants will receive their compensation administered via the Prolific platform electronically.
5. We will take the necessary steps to protect your privacy. Further, we will not collect any personally identifiable information, and your identity will not be revealed in any publications that may result from this survey. In rare instances, a researcher's study must undergo an audit or program evaluation by an oversight agency (such as the Office for Human Research Protection) that may lead to the disclosure of your data and any other information collected by the researcher.
6. Apart from the specified compensation, no additional direct benefits are provided, nor should any costs for survey participation be anticipated.
7. Participation in this study is entirely optional. You have the freedom to opt out of the study or withdraw your consent at any point during the survey.
8. If you have any questions or concerns regarding this study, or if any problems arise, you may call or email the Principal Investigator, Sachin Sharma, DBA student, ss2tk@umsystem.edu 404-654-7925 or the faculty advisor, Dr. Vivek K. Singh, Assistant Professor, vsingh@umsl.edu, 813-580-9131. You may also ask questions or state concerns regarding your rights as a research participant to the University of Missouri–St. Louis Office of Research Compliance, at 314-516-5972 or irb@umsl.edu.

9. You will receive a copy of this consent form for your records by clicking here (insert a hyperlink here for this document). We appreciate your consideration to participate in this study.

   Y/N (no signature collected

Appendix C: Demographic Background

Instructions: Please answer the questions below about your demographic information:

1. Do you work full-time?
   a. Yes
   b. No
2. What is your age (in years)?
   a. Under 20
   b. 21-25
   c. 26-30
   d. 31-35
   e. 36-40
   f. Over 41
3. Do you use e-commerce platforms for shopping?
   a. Yes
   b. No
4. What is your gender?
   a. Male
   b. Female
   c. Non-binary/ third gender
5. What is your ethnicity?
   a. White
   b. Black
   c. Asian
   d. Hispanic
   e. Others
6. What is the highest academic degree you have earned?
   a. Less than high school
   b. High school grad
   c. Undergraduate
   d. Graduate
7. What is your income level (in USD per annum)?
   a. Below $30,000
   b. $30,000- $50,000
   c. $50,000-$100,000
   d. Above $100,000
8. Please select the type of location where you currently live:
   a. City
   b. Sub-urban
   c. Rural

9. What is your overall e-commerce (platform) usage experience (years)?
    a. Less than 1
    b. 1-2
    c. 2-5
    d. 5-10
    e. More than 10

10. What percentage (%) of your monthly shopping budget is spent on online shopping platforms?
    a. 0-10
    b. 10-25
    c. 25-50
    d. 50-70
    e. Above 75

11. Do you have a paid subscription to the most frequently used e-commerce platform that you use for online shopping?
    a. No
    b. Yes
12. How many times do you shop on an e-commerce platform in a month?
    a. 0-1
    b. 2-3
    c. 4-5
    d. More than 5
13. Please name the e-commerce platform that you use most frequently.
    a. __________

Appendix D: Measurement Scales

After completing the camera decision task, participants encountered measurement items for three variables within the questionnaire. These items were evaluated using a seven-point Likert scale, where 1 represented "strongly disagree" and 7 "strongly agree," with certain exceptions noted.

Perceived Fairness (Revised from Shin, 2021)

1. The recommendation algorithm does not discriminate against customers by promoting its favored products.
2. The source of data throughout the recommendation system and its data sources should be identified, logged, and benchmarked.
3. The recommendation algorithm follows an impartial process without any prejudice to recommend products.
4. The recommendation algorithm does not promote products against the customers' best interests.
5. The recommendation algorithm is fair to the customer.

Distrust (Wang et al., 2018)

1. This recommendation system is designed to exploit customers' vulnerability given the chance.
2. This recommendation system is designed to engage in harmful behavior to customers to pursue its own interest.
3. This recommendation system is designed to operate in an irresponsible manner.
4. This recommendation system is designed to perform the business with customers in a deceptive way.
5. This recommendation system's recommendations to me are fraudulent.
6. This recommendation system is capable of engaging in harmful behavior by recommending biased products.
7. This recommendation system has the ability to maliciously manipulate the products recommended.
8. This recommendation system is capable of deceiving users by recommending biased products.
9. I suspect that this recommendation system is interested in just its own well-being, not mine.

Appendix E: Scales Adopted for Constructs

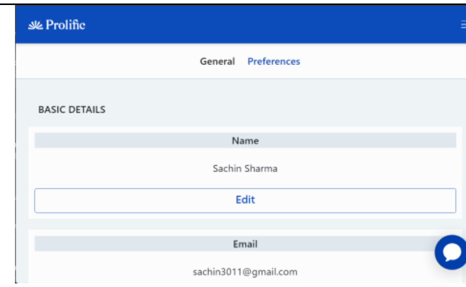
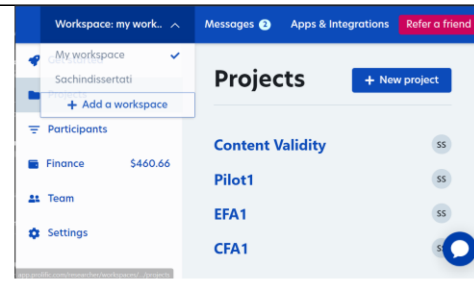
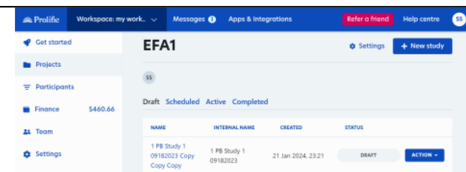
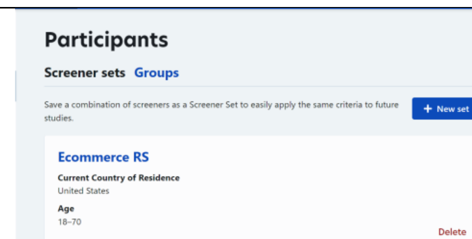
Table 27 Scale for Perceived Fairness

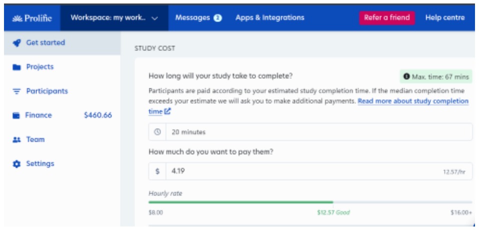
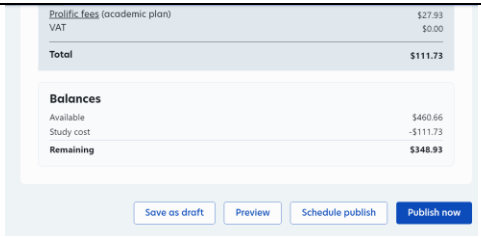
Study	Construct Name	Context	Revised scale
Shin (2021)	Perceived Fairness	Surveyed customers who shopped online	1. The recommendation algorithm does not discriminate against customers by promoting its favored products. 2. The recommendation algorithm follows an impartial process without any prejudice to recommend products.* 3. The recommendation algorithm does not promote products against the customers' best interests. 4. The recommendation algorithm is fair to the customer. *

Table 28 Scale for Distrust

Study	Construct Name	Measurement	Revised scale
Wang et al., 2018	Distrust	Distrust is the opposite of trust and refers to a lack of confidence, or faith in a person, group, organization, or system.	1. This recommendation system is designed to exploit customers' vulnerability given the chance. 2. This recommendation system is designed to engage in harmful behavior to customers to pursue its own interest. 3. This recommendation system is designed to operate in an irresponsible manner. 4. This recommendation system is designed to perform the business with customers in a deceptive way. 5. This recommendation system's recommendations to me are fraudulent. 6. This recommendation system is capable of engaging in harmful behavior by recommending biased products. 7. This recommendation system has the ability to maliciously manipulate the products recommended. 8. This recommendation system is capable of deceiving users by recommending biased products. 9. I suspect that this recommendation system is interested in just its own well-being, not mine.

Appendix F: Steps for Data Collections

Step Number	**Step Title**	**Description & Key Actions**	**Screenshot**
1	Account Setup	Register for a new Prolific account. Complete profile and verify account	
2	Create New Project	Project is used to group studies by theme, thesis and team. Studies are created and managed within projects.	
3	Create New Study	New studies are created under the project	
4	Participant Recruitment	Specify participant demographics and screening criteria. Set the number of participants needed.	

5	Pricing and Funding	Set u p the compensation rate for participants. Fund the study through the Prolific platform.	
6	Publish and Monitor Survey	Publish the survey on Prolific. Monitor participation and response rates. Communicate with participants if needed.	
7	Data Collection	Collect responses as participants complete the survey. Ensure data integrity and privacy.