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Interplay of AI and Expert Advice: Evaluating Recommendation Characteristics and Their Physiological Mediators in User Adoption

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Résumé

Ce mémoire examine l'impact des caractéristiques des recommandations provenant de systèmes basés sur l'intelligence artificielle (IA) et de conseils d'experts, sur leur adoption. Avec l'essor du commerce électronique, les e-commerçants s'appuient de plus en plus sur ces systèmes pour aider les consommateurs à naviguer parmi une multitude d'options en ligne. Bien que les avantages des recommandations multi-sources soient reconnus, peu d'études ont exploré leur influence simultanée sur la prise de décision des utilisateurs. Cette étude comble cette lacune en analysant la réponse des utilisateurs aux conseils contradictoires de ces sources, l'impact de l'explicabilité des recommandations et l'effet de l'indication de la source sur leur acceptation. Elle explore également le rôle médiateur de la charge cognitive et de l'état émotionnel dans l'adoption des recommandations. Le mémoire débute par une revue de littérature qui identifie les lacunes dans les domaines de la prise de décision en ligne et des recommandations. Le second article présente une étude empirique menée en laboratoire avec 30 participants interagissant avec une plateforme de streaming de films qui fournissait simultanément des recommandations provenant d’un agent de recommandations IA et d’experts. Les résultats montrent que l'explicabilité améliore l'adoption des recommandations, que les recommandations convergentes sont plus adoptées que les divergentes, et que l'indication des sources augmente la charge cognitive et impacte les réponses émotionnelles. De plus, une hausse de la charge cognitive s'est avérée réduire l'adoption des recommandations. Ces découvertes enrichissent la compréhension des interactions des utilisateurs avec les recommandations en ligne multi-sources et soulignent les pistes de recherche futures.

Mots clés: système de recommandation, commerce électronique, émotion, charge cognitive, explicabilité, convergence, adoption des recommandations, sources de recommandation, expert, indication de la source

Méthodes de recherche: expérience de laboratoire, données comportementales, données physiologiques

Abstract

This thesis investigates the impact of various recommendation characteristics on the adoption of dual-source recommendations, combining artificial intelligence (AI)-based advice and expert advice. The growth of e-commerce has led to an increased reliance on recommender systems by e-tailers to aid consumers in navigating the plethora of online options. In certain instances, advice generated by AI recommender systems is simultaneously presented alongside expert advice. While existing research highlights the benefits of multi-source recommendations, there is a lack of studies exploring the simultaneous influence of AI and expert recommendations on user decision-making. Specifically, this study addresses the gap in understanding the user response to conflicting advice from these dual sources. Moreover, it extends its investigation to include the influence of recommendation explainability and the effect of labeling the source on user acceptance. Additionally, this study investigates the mediating roles of cognitive load and emotional state in the acceptance of recommendations, areas that remain underexplored in the current literature. This thesis begins with a literature review identifying research gaps within the domains of online decision-making and recommendations. The second article reports on an empirical study conducted in a laboratory, where 30 participants interacted with a simulated movie streaming platform providing dual-source recommendations from AI recommender systems and experts. The findings reveal that higher explainability in recommendations enhances user adoption, and convergent recommendations lead to greater adoption compared to divergent ones. Additionally, both source labels and convergent recommendations affect cognitive load and emotional responses. Lastly, an increase in cognitive load is associated with lower adoption of recommendations. This research advances understanding of user interactions with online multi-source recommendations and highlights future research directions.

Keywords: recommender system, e-commerce, emotion, cognitive load, explainability, convergence, recommendation adoption, recommendation sources, expert, source indication

Research methods: laboratory experiment, behavioral data, physiological data

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List of Acronyms

AI: Artificial intelligence

AOI: Areas of interest

CAGR: Compound Annual Growth Rate

EDA: Electrodermal Activity

E-tailers: Electronic retailers

IA: Intelligence artificielle

REB: Research Ethics Board

RS: Recommender System(s)

S-O-R: Stimulus Organism Response

UX: User Experience

vmPFC: Ventromedial Prefrontal Cortex

XAI: Explainable Artificial Intelligence

Foreword

The present work was completed as part of the student's Masters in User Experience at HEC Montréal. This thesis has been approved by the Academic Affairs office of the Master of Science program. Further, the authorization to write this thesis in the form of articles was provided by the program director. Every co-author has granted their approval for the incorporation of each article into this thesis. The research project presented in this thesis received approval from the Research Ethics Board of HEC Montréal in June 2022, bearing the project number 2023-5114. This certification confirms that the research involving human subjects has been conducted with full ethical integrity.

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Most importantly, I extend my heartfelt gratitude to Allah for guiding me and granting me the strength, wisdom, and opportunity to be where I am today. This journey has been a testament to faith and perseverance which I am forever grateful for.

فَإِنَّ مَعَ ٱلْعُسْرِ يُسْرًا إِنَّ مَعَ ٱلْعُسْرِ يُسْرًا

القرآن الكريم 94:5-6

Chapter 1: Introduction

1.1 Context

The growth of e-commerce is exemplified by the expanding global market, with sales forecasted to surge from an estimated $5.8 trillion in 2023 to over $8 trillion by 2027, representing a growth of 39 percent (Statista, 2024). Moreover, as of 2023, e-commerce accounts for approximately 19.4% of global retail sales, and this figure is expected to rise steadily, reaching 22.6% by 2027 (Statista, 2024). By 2028, global online retail penetration is expected to climb to 23.7% (Forrester, 2024). In some regions, penetration is even higher; for instance, countries like China and South Korea are expected to see over 40% of total retail sales conducted through e-commerce by 2028 (Forrester, 2024). Within this expanding digital marketplace, consumers are frequently confronted with an overabundance of choices, a condition known as choice overload (Manolică et al., 2021). Choice overload refers to the paradox where an abundance of options can lead to increased anxiety and difficulty in decision-making, ultimately resulting in decreased satisfaction (Iyengar & Lepper, 2000). In response to this challenge, Recommender Systems (RS) have emerged as a pivotal tool in mitigating choice overload (Fayyaz et al., 2020). These systems intelligently filter and present a subset of items to users, thus simplifying decision-making processes. RS are particularly effective in e-commerce environments for enhancing user experience by reducing the complexity and cognitive load associated with large product assortments (Xiao & Benbasat, 2007). By offering personalized suggestions based on user preferences and past behavior, RS play a crucial role in guiding consumers through overwhelming options, thereby enhancing satisfaction and facilitating decision-making in the digital marketplace.

The significance and reliance on recommender systems are anticipated to grow exponentially; the market for these engines is projected to leap from $3 billion in 2021 to a staggering $54 billion by 2030, marking a Compound Annual Growth Rate (CAGR) of 37% (Straits Research, 2022). This growth projection not only reflects the current demand for personalized shopping experiences but also suggests that recommendation engines will be even more integral to navigating the future e-commerce landscape. By enhancing the shopping experience through personalized and relevant suggestions, these systems have become a cornerstone of consumer engagement and retention strategies in online retailing.

Recommender systems, heavily reliant on advancements in AI, are highly popular in the realm of e-commerce (Abumalloh et al., 2020; Benbasat et al., 2020; Bigras et al., 2019; Ghasemaghaei, 2020; Xiao & Benbasat, 2014; Xu et al., 2020). However, e-tailers also employ other forms of recommendation that do not necessarily depend on AI, drawing instead from various other sources such as consumer feedback (Chen & Xie, 2008; Yi et al., 2019) and product expert advice (Wang & Doong, 2010). Expert advice holds particular significance, similar to AI-based recommender systems, as it evaluates consumer preferences to offer tailored recommendations. Moreover, the statistical evidence overwhelmingly supports the significance of personalized recommendations in shaping consumer behavior. Forbes (2020) reports that an impressive 91% of customers are more inclined to buy from brands that offer personalized recommendations. This effect is further supported by the fact that 92% of shoppers are likely to complete their purchases once they add personally recommended items to their carts. In the same line of thought, the anticipation of tailored experiences is becoming a norm, with 67% of consumers expecting brands to provide relevant recommendations, according to McKinsey (2021). This trend is so influential that 78% of customers are not only more inclined to repurchase, but also to advocate for brands that cater to their individual preferences. Additionally, 71% of consumers look forward to personalized products and services, and 76% experience dissatisfaction when such personalization is absent (McKinsey, 2021).

Many electronic retailers (e-tailers) now incorporate RS on their platforms to assist in user decision-making, yet there is an emerging trend of platforms utilizing dual recommendation sources for more diverse and comprehensive guidance. For example, Goodreads, a renowned book recommendation site, combines algorithmic suggestions based on user preferences with community reviews and ratings, offering a blend of tech-driven and human insights. Similarly, Netflix employs a recommendation system enriched by in-house expert recommendations, presenting viewers with both algorithm-based suggestions and curated lists like “Netflix Originals”. In the realm of music, Spotify stands out by merging its algorithmic playlists, such as

“Discover Weekly”, with expert-curated and community-created playlists. TripAdvisor, a giant in travel and hospitality, integrates user reviews with personalized algorithm-driven recommendations. Etsy, a website catering to people looking for handmade and vintage items, employs algorithms for product suggestions while also presenting editor-picked items. YouTube, the video streaming platform, not only relies on its recommendation algorithms but also features content curated by creators and its editorial team. In the beauty retail sector, Sephora blends personalized product recommendations derived from user data with expert beauty advice. Lastly, Zomato, a popular food delivery and restaurant discovery platform, combines user reviews and ratings with algorithmic suggestions, complemented by collections from experts such as “Best of” lists. These examples demonstrate the use of hybrid recommendations across diverse sectors.

Past research indicates that the origin of a recommendation plays a pivotal role, often exerting a greater effect on how the recipient perceives the message than the content of the message itself (Metzger et al., 2010). Numerous studies have enhanced the understanding of the impact different sources of recommendations have (Benlian et al., 2012; Senecal & Nantel, 2004; Wang & Doong, 2010; Wang & Benbasat, 2016; Wang et al., 2018; Xu et al., 2017, 2018). Although there is a clear trend showcasing the use of dual sources of recommendations online, these studies typically involve subjects being exposed to only one source of recommendation on a website, leaving a gap in research regarding the effects of simultaneous recommendations from multiple sources (Xu et al., 2020).

The limited research on multiple simultaneous recommendations highlights the need to explore how users navigate the complexity of receiving advice from both AI recommender systems and human advisors, an area where existing studies offer conflicting insights. Indeed, some studies suggest a preference for algorithmic advice over human advice (Logg et al., 2019; Mesbah et al., 2021), while other studies seem to offer opposing viewpoints (Castelo et al., 2019; Lee, 2018). This discrepancy highlights a research gap, underlining the need to further examine how users might respond when faced with both human and algorithmic advice simultaneously. Research on user reactions to simultaneous recommendations from various sources is limited. To date, only a handful of studies, specifically two known to the researchers, have delved into this area.

It is essential to study how to provide the best user experience (UX) when users are faced with dual sources of recommendations. The design of online recommendations with an optimal UX is crucial, as it directly influences user satisfaction and engagement. Konstan and Riedl (2012) emphasize that RS should not only be accurate in their suggestions but also present these recommendations in a manner that enhances the overall user experience. This encompasses ease of use, intuitive interfaces, and providing explanations for recommendations, which have been shown to increase trust and user satisfaction (Knijnenburg et al., 2012). Furthermore, scholars argue that a well-designed RS should balance between offering novel items and reflecting the user's established preferences, thereby maintaining a level of user interest and discovery (Pu et al., 2011). The importance of UX in RS is also highlighted in terms of personalization, as personalized user interfaces can significantly improve user engagement and satisfaction (Tintarev & Masthoff, 2015). By prioritizing user-centric design principles, RS can deliver a more engaging and satisfactory experience, thereby fostering longer-term user retention and loyalty. Hence, it is important to understand what aspects of RS design lead to better UX.

Further, it is important to understand what characteristics of online recommendations lead to their acceptance. Driving the adoption of online recommendations is vital for both user satisfaction and business success. When users accept and value recommendations, it not only enhances their overall experience, leading to increased loyalty and repeat usage (Konstan & Riedl, 2012), but also directly contributes to higher sales and conversions in commercial contexts (Jannach & Hegelich, 2009). Therefore, fostering recommendation adoption is key to improving user experience and driving business performance.

1.2 Research Objective and Questions

This research examines how various characteristics of dual-source online recommendations affect user adoption, thereby filling a notable gap in the existing literature. A significant goal is to explore the roles of cognitive load and emotional state in this context. By investigating these aspects, the study seeks to provide a deeper understanding of the psychological factors influencing user interactions with AI and expert-driven recommendations. This approach is designed to enhance both theoretical knowledge and practical application in the field of online recommendations. Building on these objectives, the following research questions have been formulated to guide this investigation:

1. To what extent do the characteristics of recommendations influence their adoption when users receive simultaneous recommendations from AI-based systems and human experts? With specific attention to:

a) Recommendation convergence
b) The presence of a source indication
c) The level of explainability

2. Are there mediating mechanisms through which physiological factors influence the relationship between recommendation characteristics and the adoption of the recommendation? Specifically, this study seeks to elucidate the roles of:

a) Cognitive load: How does the cognitive load imposed by recommendation characteristics affect recommendation adoption?
b) Emotional state: How does the emotional state (valence and arousal) resulting from recommendation characteristics affect recommendation adoption?

1.3 Research Contributions

1.3.1 Theoretical Contributions

This study contributes significantly to the theoretical landscape by exploring an under-researched area of how individuals react to simultaneous recommendations from AI systems and human experts. Beginning with a review of existing literature, key research gaps in the domain of online recommendations were identified, especially those that involve both AI and human expertise. The literature review revealed a notable lack of understanding regarding users' reactions to simultaneous advice from these sources within digital platforms. It also highlighted the limited insights into user behavior when presented with conflicting recommendations and the strategies employed to integrate and resolve such discrepancies. Further, the literature indicated fluctuating preferences between AI and human advice, suggesting that such decisions are context-specific.

Additionally, unresolved questions about the ideal level of AI explainability and its effects on cognitive load and comprehension were highlighted. These insights highlight the need for further research to refine online recommendations and enhance user decision-making in online settings.

The empirical investigation offered new understanding on how users respond to AI-driven and expert advice. The findings reveal a clear preference for convergent recommendations from AI and human experts (i.e., instances where both AI systems and human experts provide matching advice to the user), demonstrating a higher likelihood of user acceptance when the advice aligns, as found in previous studies (Xu et al., 2020). Further, explainability was found to play a critical role in fostering recommendation acceptance, with clearer explanations correlating with higher adoption rates. This aligns with existing scholarly findings that note the importance of explainability in the user decision-making process (Adomavicius & Tuzhilin, 2005; Cramer et al., 2008; Rzepka & Berger, 2018; Sinha & Swearingen, 2002; Wang & Benbasat, 2007; Zanker, 2012). The presence of source labels was found to increase cognitive load. Conversely, convergent recommendations reduce cognitive load, whereas divergent recommendations (i.e., when AI systems and human experts offer differing or contradictory advice to the user) increase it. Contrary to previous studies (Aljukhadar et al., 2012; Bettman et al., 1990; Bettman et al., 1998), findings suggest that an increase in cognitive load is inversely related to the likelihood of recommendation adoption. Furthermore, convergent recommendations were shown to lead to a lower emotional response, characterized by decreased emotional arousal and more negative valence. Additionally, the presence of source labels appeared to decrease emotional valence. This research is essential for advancing the existing literature on human-computer interaction and decision-making, providing a deeper understanding of the interplay between technology design elements and user behavior.

1.3.2 Managerial Implications

This study aims to provide managerial insights that are both practical and impactful. Insights gained into the impact of various recommendation characteristics on user adoption can significantly inform the design and development of more effective online recommendations. The results of this study highlight significant considerations for how businesses deploy AI and expert recommendations. There is a clear user preference for consistency in recommendations between AI-driven recommendations and human expertise. This highlights the necessity for managers to combine these two recommendation sources, which in turn fosters greater recommendation adoption. Additionally, this research emphasizes the essential role of transparency and the need for explainability within AI systems. Businesses that commit to developing AI recommendations that are both transparent and easy to understand stand to gain a competitive advantage, as consumers increasingly value understandable systems. Moreover, the findings indicate that convergent recommendations from both AI and human experts can lower cognitive load, simplifying the decision-making process for users. Managers are advised to integrate convergent AI recommendations alongside human expertise to streamline decision-making processes, thus reducing cognitive load and improving the user experience.

1.4 Personal Responsibilities and Contributions

This research was conducted as part of the student's master's thesis project, under the invaluable guidance of the student's research directors and with significant support from the Tech3Lab research team. Table 1.1 presents the individual efforts of the student in completing their master's thesis. It provides a breakdown of the critical stages in the thesis development process, including the specific tasks carried out and the student's contribution, expressed as percentages. These figures exclude the guidance and contributions from the co-directors throughout the project.

Table 1.1 Student's Contribution and Responsibilities in the Realization of This Thesis

Steps in the process	**Contribution**
Research questions	Identifying gaps in current literature and defined the research problem - Identified the problem and its implications - **90%** • Defined research questions • Identified the constructs to be tested

Literature review	Conducting relevant research, read scientific articles related to the constructs and topic, and write the literature review - **100%**
Conception and experimental design	Designing the experimental protocol - **90%** • Ethics approval: Prepare the required documentation for the REB. • Develop experimental design • Design the stimuli • Write the research protocol for data collection.
Recruitment of participants	Recruiting participants for the study – **90%** • Develop participation criteria, recruitment documentation and consent forms. • Schedule participants • Communication with participants • The participant compensation and the distribution of experiment invitations to panel members from the institution's email list were managed and conducted by the research team.
Data collection	Conduct data collection - **90%** • Manage data collection including technical setup, tools installation (EDA), and physiological signals calibration / verification. • Moderate the experiment • The experiment room was set up by the research team.
Analysis	Conduct data analysis- **50%** • Add markers and organize data for enhanced granularity. Add areas of interest (AOI) onto the stimuli. • Prepare a plan for statistical analysis. • Extraction of data was done by the research team. • Statistical tests were performed by the lab statistician. • Statistical tests interpretation.

Writing the thesis	Writing the articles and thesis - **100%** This was done with the guidance and help of the co-directors, thus allowing to perfect this thesis.

1.5 Thesis Structure

This thesis is structured in the form of articles. The present chapter, Chapter 1, serves as an introduction to this thesis. It provides a contextual framework for the research issues being addressed and outlines the research questions that will be explored through the empirical study conducted. Chapter 2 offers a comprehensive literature review, summarizing the existing state of research. It defines crucial concepts and constructs related to the research questions previously mentioned, and pinpoints gaps in the existing literature. Certain of these identified gaps will be the focus of the study conducted within this thesis.

Chapter 3 presents an empirical investigation conducted in a laboratory setting. This chapter is dedicated to addressing the two research questions previously outlined, delving into the influence of distinct characteristics of recommendations – namely, the convergence of recommendations, the degree of explainability, and the explicit indication of the source – on their adoption. Additionally, it explores the mediating effects of cognitive load and emotional state on the acceptance of these recommendations. The proposed hypotheses, methodology, and results will be provided, followed by a discussion on the implications and limitations of the research.

Chapter 4 serves as the conclusive chapter of this thesis. It begins with a recapitulation of the methodology employed in the empirical laboratory study. This is followed by a reminder of the research questions and a summary of the key findings. The chapter then concludes with the theoretical contributions arising from the study, as well as the practical implications for management.

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Chapter 2: Literature Review

2.1 Introduction

The objective of this literature review is to examine scholarly work related to consumer decision-making processes, with a particular focus on online settings and the use of online recommendations as tools to aid in such decisions. This review evaluates the impact of emotions on decision-making and addresses the prevalent challenge of information overload, a phenomenon where consumers are flooded with an excessive amount of data. The effectiveness of recommendations from recommendation systems (RS) and human experts in addressing information overload is analyzed, alongside an examination of the dynamics that occur when consumers are presented with both sources of advice simultaneously. Additionally, the various determinants that impact users' acceptance of the recommendations provided to them are explored. The review also identifies gaps in the current literature, pinpointing areas that require further empirical investigation to enrich comprehension of consumer decision-making in the context of online platforms.

The search strategy to conduct this literature review involved a layered screening process, beginning with an analysis of titles and abstracts to assess relevance, followed by a detailed examination of the full-text articles to evaluate their contribution to the core topics and the constructs. Priority was given to peer-reviewed articles, meta-analyses, and empirical studies. In order to identify suitable papers, searches incorporating pertinent keywords were performed across a range of international databases. These databases were carefully selected for their reputable academic resources and publishers. Additionally, searches extended to various international journals and a selection of key conference proceedings. Details on the search queries are presented in Table 2.1. In conducting these searches, Boolean operators "OR", "AND", and "NOT" were utilized to refine and focus the queries.

Table 2.1 List of Search Keywords and Scientific Databases Used to Research the Constructs

Search keywords	**Scientific databases**
"Affective Response to Technology" "AI-based Recommendation Systems" "Algorithmic Recommendations" "Cognitive Load" "Cognitive Load and Decision-making" "Consumer Online Decision Making" "Conflicting Advice" "Emotional Affect" "Emotional Affect in Online Shopping" "Emotional Response to Online Recommendations" "Emotions in Decision Making" "Explainable AI" "Explainable Artificial Intelligence" "Explanation in Recommender System" "Explainability in AI Systems" "Explainability in Recommendations" "Expert Advice" "Expert-driven Recommendation Systems" "Expert-driven Recommendations" "Explanation in Recommendation Systems" "Online Decision-making" "Recommendation Acceptance" "Recommendation Agent" "Recommendation Convergence" "Recommendation Divergence" "Recommendation System" "Recommendation System Adoption" "Recommendation Systems" "Recommender System" "Source Credibility" "Source Credibility in Online Recommendations" "Source Indication in Recommendations" "Transparency of Algorithms" "User Acceptance of Recommendations" "User Experience and Recommendation Systems" "User Experience and Cognitive Load" "Valence and Arousal"	ABI/INFORM Collection (Proquest) ACM Digital Library APA Psych Net Association for Information Systems Transactions on Human-Computer Interaction Frontiers in Psychology Google Scholar IEEE Xplore Information Systems Journal Information Systems Research International Journal of Human–Computer Interaction Journal of Consumer Behavior Journal of Consumer Psychology Journal of Information Technology Journal of Management Information Systems Journal of the Association for Information Systems Management Information Systems Quarterly PsycINFO Pubmed ScienceDirect Scopus SpringerLink TandF Online Web of Science

2.2 Consumer Decision-Making

Humans make decisions daily, ranging from automatic actions like turning on a light to more significant choices like careers and marriage. Despite their diversity, the decision-making process remains consistent. However, individuals may not always recognize the subconscious steps in this process or the factors influencing their choices (Willman-Iivarinen, 2017). Consumer decision-making refers to the cognitive process through which individuals or groups of individuals evaluate, select, and purchase products and services to satisfy their needs and wants, while considering various factors such as preferences, available information, perceptions, and external influences (Solomon, 2018).

Engel, Kollat, and Blackwell (1968) introduced a consumer decision-making model, often referred to as the EKB model. This framework characterizes the process by which consumers make choices from among various available alternatives. While scholars have proposed several theories and models related to consumer decision-making (Keeney, 1982; Nicosia et al., 1966; Sheth et al., 1991; Simon, 2000; Smith & Rupp, 2003) the EKB model enjoys widespread acceptance within academia and is acknowledged as a substantial contribution to the field of consumer behavior as it continues to be used in various studies (Ashman et al., 2015; Darley et al., 2010; Karimi et al., 2015; Liang & Lai, 2002). The decision process component of the EKB model is known as the conventional and widely known *Five-stage model of the consumer buying process* (Stankevich, 2017). It comprises five stages that individuals go through when making a purchase of a product or service.

To specify further, it begins with problem recognition, where a consumer identifies a need or issue that can be resolved through a purchase. This requirement may arise from either internal factors like personal desires, or external factors such as advertising and recommendations from acquaintances. Following problem recognition is the information search phase, during which consumers gather information from diverse sources, including personal experiences, social networks, online reviews, advertisements, and expert opinions. Subsequently, consumers move on to the evaluation of alternatives stage, where they discern between multiple options based on various attributes like price, quality, brand reputation, and features, weighing these attributes in accordance with their personal preferences. After the evaluation, a purchase decision is made, considering factors like budget constraints, product availability, and incentives such as discounts or promotions. Finally, post-purchase evaluation occurs, during which consumers assess their satisfaction with the product or service (Kimmel, 2018; Solomon, 2020).

In the context of e-commerce, these stages of the consumer decision-making process take on new dimensions, particularly in the information search and evaluation of alternatives stages. The digital environment of online shopping offers an expanded array of choices and information sources, which can significantly influence consumer behavior (Laudon & Traver, 2023). In e-commerce, problem recognition can often be triggered by digital marketing tactics such as targeted advertisements, email marketing, and social media promotions, which are designed to create a perceived need or desire in potential customers (Chaffey & Ellis-Chadwick, 2019).

During the information search phase in online settings, consumers have access to a wealth of information, including product descriptions, customer reviews, ratings, and price comparison tools. This abundance of information, while beneficial, can also lead to the challenge of information overload, making it more difficult for consumers to process and make decisions (Bawden & Robinson, 2009). Empirical studies have shown that online reviews and ratings significantly impact consumer choices, as they provide social proof and reduce uncertainty about product quality (Cheung & Thadani, 2012).

The evaluation of alternatives in the online context is also nuanced, as consumers are not only comparing product attributes but also the credibility and usability of e-commerce platforms. Factors such as website design, ease of navigation, and the perceived security of the transaction play crucial roles in influencing consumer decisions (Liu & Forsythe, 2011). The role of brand reputation and online presence has also been emphasized in studies by Hsiao et al. (2010), highlighting the importance of a strong digital brand image in attracting and retaining online consumers.

In the purchase decision stage, online consumers are influenced by additional factors such as shipping costs, delivery times, and return policies, which are unique to the e-commerce environment (Koufaris, 2002). The final stage, post-purchase evaluation, is critical in the online context, as consumers often share their experiences through online reviews and social media, influencing the decisions of future consumers (Pentina & Tarafdar, 2014).

It is important to mention that emotions have been increasingly recognized as a pivotal factor in consumer decision-making, with numerous studies demonstrating their influence across various stages of the purchasing process. In fact, Lerner et al. (2015) have highlighted that emotions can affect the perception of information and bias the evaluations that consumers make throughout the decision-making process. Further, a study by Verhagen and Van Dolen (2011) demonstrates that consumers experiencing positive emotions while navigating an e-commerce website are more likely to engage in impulse buying. This finding is in line with the work of Shiv and Fedorikhin (1999) who found that consumers often rely on affective states as a heuristic for making quick decisions, especially when processing resources are limited. These studies collectively affirm that emotions are integral to the decision-making process.

As mentioned, the digital context introduces unique factors in the context of online decision-making. Indeed, in the age of e-commerce, the expanded array of options available to consumers online presents a paradox. While such variety offers unparalleled access to products and services, it also presents the challenge of information overload—a state where the volume of available information exceeds the consumer's capacity to process it (Jacoby, 1977). As consumers progress from the evaluation of alternatives to the crucial phase of making a purchase decision, the excessive information can hinder judgment, leading to decision paralysis or suboptimal choices (Schwartz, 2004). It is here that the efficiency of the decision-making process is most tested, as users must navigate through the noise of abundant data to discern the most relevant information for their needs (Eppler & Mengis, 2004).

2.2.1 Information Overload

The growth of e-commerce has intensified the phenomenon of information overload, where consumers are confronted with more information than they can effectively assimilate or utilize for decision-making (Jacoby, 1984). Information overload in the context of e-commerce can be defined as a state where consumers are presented with more information than they can effectively process, leading to difficulty in understanding, decision-making, and potentially causing cognitive stress. This occurs due to the vast number of choices, extensive product information, user reviews, and comparative options available online (Edmunds & Morris, 2000). The large volume of options and data in online shopping environments can lead to cognitive and emotional strain, manifesting as decision fatigue and decreased satisfaction (Schwartz, 2004). The temporal pressure in e-commerce further complicates this by limiting the time available for consumers to evaluate their options, thereby amplifying the effects of overload (Eppler & Mengis, 2004). This excess of information not only poses a challenge for consumers but also for businesses, which may find it increasingly difficult to capture consumer attention and effectively market their products amidst the noise (Roetzel, 2019).

Empirical studies have identified several antecedents to information overload in e-commerce, such as the number of alternatives presented, the complexity of information, the need for comparison, and the presence of conflicting information (Li, 2017; Liu & Wei, 2003). Consequences for consumers include reduced decision accuracy, increased decision time, and heightened levels of stress and dissatisfaction (Malhotra, 1982; Schommer et al., 2001). Businesses, on the other hand, may experience diminished marketing efficiency, lowered customer conversion rates, and challenges in maintaining customer engagement (Edmunds & Morris, 2000). These issues highlight the need for strategies to alleviate the negative consequences of information overload, ensuring that consumers can navigate the abundance of online information more efficiently and that businesses can maintain effective communication with their audience.

In the context of online decision-making, recommendations serve as an invaluable tool to mitigate the effects of information overload. These recommendations, sourced from user-generated content, expert insights, or algorithm-driven recommender systems, act as filters, sifting through the vast amount of available information to highlight the most pertinent options to consumers. This filtering is crucial in enabling consumers to navigate the decision-making process more effectively, leading to more informed and satisfying decisions (Senecal & Nantel, 2004). User-generated reviews, for instance, have been found to significantly influence purchase decisions by providing authentic customer experiences (Cheung et al., 2009), while expert reviews and recommendations lend credibility and authority to the information being considered (Gilly et al., 1998). Moreover, algorithm-based recommender systems, through personalized suggestions, have been shown to not only reduce the search costs and cognitive load associated with large product assortments, but also enhance user satisfaction by simplifying choice complexity and offering users a more enjoyable shopping experience (Häubl & Trifts, 2000; Xiao & Benbasat, 2007). Indeed, information overload in decision-making processes can lead to significant negative emotional consequences. As individuals face an excessive amount of information, they may experience increased stress, anxiety, and decision fatigue, which can hinder their ability to make well-informed decisions (Eppler & Mengis, 2004). This overload often results in a paradox of choice, where more options lead not to better choices but to greater anxiety and a less satisfying decision experience (Schwartz, 2004). Given the positive impact of recommendation systems in streamlining online decision-making, it becomes evident how such tools are crucial in alleviating the negative emotional consequences associated with information overload.

2.2.2 The Role of Emotion in Decision-Making

The intricate role of emotions in decision-making has become a fascinating subject in the realms of cognitive psychology and neuroscience, contesting the traditional view that decision-making is purely a rational process. Ground-breaking theories, such as the somatic marker hypothesis introduced by Damasio (1996), suggest that emotional responses are critical in guiding decisions, often beyond conscious awareness. Neurobiological studies offer substantial backing for this theory (Bechara & Damasio, 2005; Damasio, 1994). In fact, the effects of damage to the ventromedial prefrontal cortex (vmPFC), a crucial area in the brain for processing emotions, have shown to impact decision-making. These studies have demonstrated that impairments in this region can result in difficulties in personal and social decision-making capacities, despite maintaining the ability of overall problem-solving skills. This connection is also explored by Bechara and Damasio (2005) who found that individuals with vmPFC damage often make detrimental long-term decisions despite understanding the risks involved in their decisions. Their research emphasizes that cognitive awareness alone is insufficient for sound decision-making; instead, emotional insights, or somatic markers, are essential for choices that impact personal and future well-being.

Moreover, Bechara and Damasio's (2005) work points out that not just the existence of emotions, but their specific nature, exerts a significant influence on the choices individuals make. Emotions are generally characterized by two main dimensions: valence and arousal. Valence is the inherent appeal (positive valence) or unpleasantness (negative valence) associated with an emotional event, whereas arousal describes the physical and psychological activation it triggers (Russell, 1980). These dimensions significantly influence cognitive processes; for instance, studies demonstrated how specific emotions, such as fear (negative valence, high arousal) and anger (negative valence, but differing in arousal), distinctly affect judgment and decision-making (Lerner et al., 2015). These findings highlight the complexity of emotions, challenging the notion of their role as merely irrational factors, and illustrating their capacity to both hinder and facilitate decision-making. The nuanced understanding of how emotional states can direct decision-making processes is reshaping views of the mind's workings, providing new avenues for exploring human behavior and decision-making (Norman, 2004).

In the realm of e-commerce, emotions are a significant driver in online decision-making. Experiencing negative emotions during an e-commerce site visit can lead customers to discontinue their shopping activity, exiting the site without finalizing their purchases. Beyond the immediate impact of lost sales, such negative interactions can also have enduring effects for the retailer in the long-term (Gao & Wu, 2010; Hasan, 2016; Thota, 2012). The affect-as-information theory suggests that emotions are integral to the decision-making and evaluation processes (Schwarz & Clore, 1983). This perspective holds that individuals use their emotional reactions as indicators for making choices. For example, a sense of joy when interacting with a new product may be interpreted as indicative of its quality, which could influence a decision to buy it. On the other hand, feelings of discomfort might serve as a warning, leading a person to question or avoid a particular choice. In this way, emotions provide cues that shape how individuals respond to and think about their environment and different situations (Pham, 2007).

Different factors surrounding an online experience can lead to various affective states. For instance, empirical studies have consistently shown that emotions elicited by the user experience of a website can profoundly influence consumer behavior, guiding decisions from initial interest to final purchase (Indiani & Fahik, 2020; Kim & Lennon, 2013), and affecting engagement and satisfaction levels (Desmet & Hekkert, 2007). In fact, Eroglu et al. (2001) state that the user interface and user experience are pivotal in evoking emotions within users as they navigate an e-commerce site. These elements are essential, as they shape user satisfaction and, by extension, influence the site's success (Sahi, 2015; Yigit et al., 2022). Further affirming this, the research has found that the virtual environment provided by an e-commerce site plays a decisive role in forming user emotions and attitudes, which are critical determinants of purchasing behaviors (Eroglu et al., 2001). In a supportive vein, Makkonen and colleagues (2019) observed that successful sales are commonly associated with the presence of positive emotions among customers. Their findings suggest that positive emotional experiences are significantly correlated with enhanced customer satisfaction, increased probability of repeat purchase, and a greater inclination to recommend the service or product, as opposed to negative emotions (Makkonen et al., 2019).

In the competitive e-commerce landscape, customers can easily switch to a different online retailer. Therefore, as e-commerce continues to evolve, the need for creating emotionally resonant online experiences becomes ever more apparent (Wu et al., 2014). A positive emotional experience is not just a value-added aspect of e-commerce; it is an integral component that can determine the success of the website in a competitive digital economy.

2.3 Online Recommendations

Consumers have historically relied on advice and suggestions from peers to inform their purchasing choices. In an experimental study conducted by Çelen, Kariv, and Schotter (2010), it was observed that individuals followed the recommendations they received 74% of the time. In the decision-making process, consumers frequently encounter the opinions and suggestions of others. These recommendations are typically explicit, with consumers advising one another on preferred product choices (Peluso et al., 2017). Moreover, such recommendations frequently include detailed descriptions of the product, providing insights into what it is like to own or use it, thereby aiding other consumers in connecting the product with their specific needs (Simonson & Rosen, 2014). In general, recommendations from others serve to reduce the cognitive effort associated with decision-making and enhance the confidence in the decision outcome (Shugan, 1980). Consequently, the ease or complexity of a decision is likely to influence the degree to which a recommendation is accepted. Research has indicated that when a decision is easy, individuals are less inclined to use the advice offered by others. However, in cases of intricate decisions, individuals are more likely to adhere to recommendations as they seek additional information (Gino & Moore, 2007).

With the continuous progress of information technology and the rapid expansion of the Internet, there has been a significant expansion of the avenues through which consumers can access diverse recommendations from other entities. Senecal and Nantel (2004), identified three sources for delivering online recommendations: 1) other consumers, 2) human experts, and 3) expert systems (i.e., recommender systems). Indeed, recommender systems began with a simple insight:

people often base their everyday choices on suggestions from others (Resnick et al., 1994; Shardanand & Maes, 1995). Whether it is seeking book recommendations from friends, employers relying on recommendation letters for hiring, or individuals picking movies based on a critic's review, individuals frequently trust and follow others' advice. The initial recommender systems sought to replicate this behavior by employing algorithms that gathered recommendations from a user community, providing personalized recommendations to a user derived from the preferences of similar users (Ricci et al., 2015). In the following sections, the exploration will focus on the influence of human experts and recommender systems on online consumer decision-making.

Research has focused on the pivotal trait of source credibility in both expert recommendations and recommender systems (Cheung et al., 2009; Hovland & Weiss, 1951; Pornpitakpan, 2004). Acknowledging the importance of this characteristic, it has been observed that source credibility significantly influences how users perceive recommendations and their likelihood to conform with them (Fogg et al., 2002; Hyan Yoo & Gretzel, 2008; Metzger et al., 2010).

2.3.1 Source Credibility

Research has highlighted the significant impact of source credibility on how individuals perceive recommendations, whether they originate from humans or computer systems (Cheung et al., 2009; Hovland & Weiss, 1951; Pornpitakpan, 2004). Credibility is not an inherent trait of a source; rather, it depends on how the message recipient perceives that source (O'keefe, 2015). Therefore, source credibility is essentially the judgments made by message receivers regarding the believability of a communicator (Fogg, 2002). Reviews of studies on source credibility indicate a preference for more credible sources, seen as more persuasive (Petty et al., 1997).

Though credibility encompasses various dimensions (Buller & Burgoon, 1996; Petty, 2018) researchers agree that it primarily comprises trustworthiness and expertise (Fogg et al., 2002; Fogg, 2002; O'keefe, 2015). According to scholars, expertise refers to a source's capacity to exert influence within a particular domain (Mayer et al., 1995). Fogg et al. (2002) conceptualize expertise using terms like knowledgeable, experienced, and competent, capturing the perceived knowledge and skill of the source. Similarly, O'keefe (2015) describes expertise as competence, expertness, or qualification. Fogg (2002) outlines numerous cues that contribute to perceptions of expertise, such as labels that assert one's authority. The trustworthiness of a source encompasses attributes like moral character or personal integrity (O'keefe, 2015). Consequently, trustworthiness is frequently characterized by qualities like good intentions, honesty, and impartiality (Fogg et al., 2002). Some literature conceptualized trustworthiness in terms of benevolence and integrity (Mayer et al., 1995). Other literature highlighted several factors that influence perceptions of trustworthiness, including a source's fairness, willingness to argue against their own interests, and perceived similarity (Fogg, 2002).

In the context of decision-making, perceptions of credibility, particularly expertise and trustworthiness, act as heuristic cues that can either initiate or inhibit the deeper, more systematic processing (Chaiken, 1989; Chen & Chaiken, 1999). According to the heuristic-systematic model of information processing, individuals simultaneously engage in two distinct modes of reasoning: heuristic and systematic processing (Chaiken, 1989; Chen & Chaiken, 1999). The decision on which mode to employ is influenced by the sufficiency of heuristic cues in generating confidence in judgments. Koh and Sundar (2007) extend this framework to the domain of media technologies, noting that such technologies can activate either or both types of processing. For instance, if a shopper comes across a specialized online assistant on a retail site, they may initially be guided towards heuristic thinking by cues such as expert recommendations. Yet, should these cues prove inadequate for a confident judgment, the shopper is likely to transition to a more thorough, systematic evaluation (Sundar et al., 2007). To elaborate further, humans often use cognitive heuristics in decision-making (Meinert & Krämer, 2022). Cognitive heuristics are mental strategies that do not encompass all available information, significantly reducing the cognitive load for decision-making and judgments (Kruglanski & Gigerenzer, 2011). These heuristics serve as simple, efficient shortcuts triggered by a cue, automatically employed by individuals to guard against cognitive strain and information overload, thereby enabling efficient interaction with incoming information (Sundar et al., 2007). An important heuristic in decision-making is the expertise heuristic (Meinert & Krämer, 2022). This translates as an equation linking expertise and credibility in the mind of decision-makers (Metzger & Flanagin, 2007). This association is triggered upon receiving relevant cues that can come in various forms (e.g., credentials, area of work, titles) (Goldstein & Gigerenzer, 2002). Virtual credentials in online settings have the same impact as in the real world (Cheung et al., 2009). In the same vein, empirical evidence shows that highlighting the expertise of a source, be it through their name, role, or profession, enhances the perceived credibility of communicated information, spanning various contexts such as health-related tweets, social media posts, and online reviews (Hu & Shyam Sundar, 2010; Winter & Krämer, 2012). Interestingly, this association operates without necessarily evaluating the content of the message from the proposed expert. Perceiving a source as experienced or having a presumed reputation automatically enhances the perceived credibility of the information they communicate (Metzger et al., 2010). This process allows users to save cognitive effort that would otherwise be needed for an exhaustive evaluation of both the source and its content (Metzger et al., 2010).

The impact of source credibility findings extends to recommendations from recommender systems. Both these aspects have been extensively researched and are also discussed within the context of recommender systems (Hyan Yoo & Gretzel, 2008). The trustworthiness and expertise of recommender systems are essential for users to consider their suggestions as credible (Fogg et al., 2002). Users perceive a recommender system as trustworthy when its recommendations are seen as dependable and truthful (Xiao & Benbasat, 2007). A recommender system is recognized as an expert when users believe it has the ability and skill to offer effective recommendations (Senecal & Nantel, 2004; Xiao & Benbasat, 2007). Transparency (i.e., explainability) in the reasoning behind the recommender system's suggestions can enhance users' perception of source credibility (Sinha & Swearingen, 2002). When the logical basis behind the recommendations is explained, it builds trust and exhibits the expertise of these suggestions (Pu & Chen, 2006).

Moreover, the relationship between source credibility and conformity has been a subject of interest in understanding social influence and persuasion. Hovland and Weiss have identified a direct link between the credibility of a source and the perceived credibility of its message, suggesting that such credibility is a pivotal factor in the message's persuasive power (1951). This relationship extends into the digital realm, particularly in online environments such as reviews and recommendations (Sussman & Siegal, 2003). Research has established credibility as a key determinant in the adoption of online recommendations (McKnight & Kacmar, 2006). When individuals consider a source to be highly credible, they are more inclined to accept and adopt the information provided (Grewal et al., 1994), particularly in making purchasing decisions (Nabi & Hendriks, 2003). Conversely, if a recommendation source is perceived as less credible, there is a corresponding decrease in the likelihood of the individual accepting and acting upon that recommendation, often to avoid potential risks (Cheung et al., 2009).

Acknowledging that trust and expertise form the basis of source credibility, it is apparent that these elements are integral in guiding users' judgments and behaviors. In the realm of decision-making, heuristics streamline the process, allowing individuals to navigate complex information landscapes with ease. These mental shortcuts, activated by specific cues, simplify the cognitive load, leading to efficient and often subconscious assessments of a source's credibility. The subsequent section will provide a more detailed examination of these cues.

2.3.1.1 Source Indication as a Credibility Cue

For recommendations to be effective as decision-making aids, users must trust the source from which the advice originates (Fogg, 2002; Xu, 2014). On platforms where consumer feedback is shared, individuals typically do not have a previous acquaintance with the reviewers whose advice they might consider. Inference theory suggests that individuals form judgments about the unknown by relying on accessible cues as their source of information (Baker et al., 2002). Without prior engagements to inform their judgment, they must deduce the reviewer's reliability from the evident attributes present (Xu, 2014).

For instance, online consumers evaluate the relevance of the source based on cues present within the review or the reviewer's profile, with expertise and trust being a notable factor influencing their decision-making process (Brown et al., 2007; Kirmani & Rao, 2000; Xie et al., 2011; Xu, 2014). Recognizing the importance of source credibility, consumers specifically look for personal details that indicate whether a reviewer is an expert or a layperson, affecting their assessment of the information's reliability (Metzger et al., 2010; Smith et al., 2005; Willemsen et al., 2012). Moreover, the presence of expertise cues such as titles or qualifications often leads to an attribution of expertise to the source, functioning effectively as labels that signal credibility and trust, even if the quality of the underlying information is not thoroughly evaluated (Taylor & Fiske, 1978). Reviews by experts, especially editors or critics, tend to be highlighted on platforms, emphasizing professional expertise, and signaling high-quality content, which resonates with consumers seeking credible information (Plotkina & Munzel, 2016; Smith et al., 2005; Zhang et al., 2010). This expertise cue not only reflects the reviewer's specialized knowledge but also contributes to the perceived value of the review (Naujoks & Benkenstein, 2020). In fact, the expertise of a source is so impactful that it can lead to greater adoption of information (i.e., conformity) from online product recommendations and can enhance consumers' intentions to make purchases (Ismagilova et al., 2020; Lis, 2013). Thus, it is beneficial for platform managers to highlight these expertise cues under the form of labels, possibly through the implementation of badges like "reviewer of the month" or "expert," to provide consumers with clear indicators of the source's expertise level (Ismagilova et al., 2020; Lis, 2013).

2.3.2 Conformity

Individuals' attitudes and actions are frequently influenced by the majority opinion (Asch, 1956; Turner, 1991). Individuals often adjust their views and behaviors to adhere to social norms, even if it contradicts their personal preferences (Cialdini & Goldstein, 2004; Haun et al., 2013; Morgan & Laland, 2012). Psychologists term this phenomenon "social conformity," where individuals adopt the opinions, behaviors, and judgments of others (Turner, 1991). According to previous research, three intrinsic motivations drive social conformity: the desire for social approval, the pursuit of making correct decisions, and the aspiration to maintain a positive self-image (Cialdini & Goldstein, 2004).

In the context of decision-making, it is widely recognized that individuals tend to align their decisions with the majority within group settings (Sherif, 1935). Similarly, research on social influence reveals a tendency for individuals' attitudes and judgments to align with the majority opinion (Asch, 1956; Nemeth, 1986; Wolf & Latané, 1983). This conformity phenomenon can result from either social pressure or the belief that the majority holds the correct opinion (Deutsch & Gerard, 1955). Deutsch and Gerard (1955) outlined two key reasons that lead people to conform: normative conformity and informational conformity. Normative conformity involves submitting to group pressure primarily to fit in or avoid rejection by the group, as seen in the Asch conformity experiment conducted in 1951 (Asch, 2016). Individuals often conform publicly to the group's views while privately maintaining differing opinions. It is a form of conformity driven by the desire for social acceptance. Asch's ground-breaking study reveals how individuals modify their judgments to match group consensus, even when they view the group's choice as incorrect (Asch, 2016). Indeed, in their study, even when participants knew the group was wrong, they went along with the group to avoid feeling uncomfortable by disagreeing or standing out. On the other hand, informational conformity typically arises when an individual lacks knowledge and seeks guidance from the group. Additionally, it occurs in ambiguous situations where people socially compare their behavior to that of the group. Here, individuals tend to internally adopt the group's views and incorporate them as their own, a process known as internalization (Sherif, 1935). This notion suggests that people conform because they perceive the majority's viewpoint as more accurate or knowledgeable.

In the same vein, it is also acknowledged that conformity may arise from a desire to enhance decision-making. Deutsch and Gerard (1955) noted the early influence of others' perceptions on one's understanding of reality, suggesting that group majorities can be viewed as valuable problem-solving aids based on past experiences (Penner & Davis, 1969). In decision-making, conformity might lead individuals to opt for the choice favored by the majority of advisors. Russo and Dosher (1983) suggested that individuals utilize the majority rule as a strategy to simplify choices and reduce cognitive effort.

2.3.3 Expert Recommendations

Oftentimes, when someone is faced with making a decision, they will seek support by discussing it with other people, including parents, friends, or experts. Specifically, experts offer valuable support for decision-making when uncertainties arise due to a lack of personal knowledge or experience (Sniezek & Van Swol, 2001). According to Bourne et al. (2014), an expert is someone who achieves a level of expertise in a certain field. They define expertise as "elite, peak, or exceptionally high levels of performance on a particular task or within a given domain" (p. 1).

Furthermore, experts have the power to persuade decision-makers. Persuasion has received considerable attention within the field of social psychology (Gilbert et al., 1998; O'keefe, 2015). Numerous studies have concentrated on examining the influential factors associated with persuasiveness, particularly those related to the person delivering the persuasive message. A prominent factor in this context is high expertise (Cialdini & Goldstein, 2004; Eagly & Chaiken, 1993; Rhine & Severance, 1970). In fact, it is reported that generally, the persuasiveness of a message tends to increase when it is conveyed by an individual with substantial expertise in the subject matter. This persuasive impact of experts is rooted in the concept that people are more likely to trust the opinions of someone presumed to possess significant and relevant knowledge (Cartwright & Zander, 1968). In a similar vein, the term "expert" inherently suggests a high level of knowledge and experience, effectively serving as an endorsement for the advice they provide (Önkal et al., 2009).

A user's acceptance of expert advice may not always be associated with a thorough examination of the advice (Dijkstra, 1999). The elaboration likelihood model, a theory of persuasion proposed by Petty and Cacioppo (1986), supports this idea by suggesting that individuals tend to form judgments based on peripheral cues when they lack motivation or the ability to critically evaluate the content of a message (Dijkstra et al., 1998). The source's persuasiveness plays a crucial role as a peripheral cue. For instance, people may trust a doctor's advice primarily because it comes from a medical professional rather than due to an in-depth evaluation of the message's content.

Hence, it is understood that the acceptance of expert advice by users, even without a rigorous examination of its accuracy or relevance, can be attributed to the persuasiveness of the expert himself (Fogg et al., 2002).

Research indicates that decision-makers tend to be more receptive to advice provided by experts rather than by those with less expertise (Harvey & Fischer, 1997; Yaniv & Kleinberger, 2000). Nonetheless, Armstrong's seer-sucker theory (Armstrong, 1980) posits that people tend to place unwavering trust in expert judgments and advice, even when substantial evidence indicates that these experts are no more accurate than individuals with basic knowledge. This phenomenon has been observed in various domains, including political forecasting (Tetlock, 2017), conflict outcome prediction (Green & Armstrong, 2007), and stock market forecasting, where experts at times exhibit forecasting performance no better than those with limited knowledge (Önkal et al., 2009). Armstrong (1980) argues that one rationale for this reliance on experts is the ability to shift responsibility; experts can be held accountable if their forecasts prove inaccurate. As noted by Bonaccio and Dalal (2006), motives such as sharing or shifting responsibility and avoiding the perception of rejecting help (Harvey & Fischer, 1997) primarily come into play when the advisor is a human. When advice is derived from an algorithm, these motives may be of reduced relevance.

2.3.4 AI Recommender Systems

As e-commerce platforms evolved, there came a crucial necessity to offer recommendations by filtering through the vast array of available options. Users encountered challenges in navigating through the extensive range of products and services on websites to make informed choices (Ricci et al., 2015). In fact, the abundance of data has also given rise to the challenge of information overload. As previously discussed in this literature review, information overload can be described as the situation in which an average individual is flooded with an overwhelming amount of data, making it difficult for them to process and make decisions (Eppler & Mengis, 2004). To tackle this issue, data mining techniques come into play by assisting in the acquisition and processing of pertinent information. One of the most commonly utilized tools among these data mining techniques is recommender systems (Jayalakshmi et al., 2022). Indeed, recommender systems have evolved into essential components in today's e-commerce applications. Xiao and Benbasat (2007) define recommender systems as “software agents that elicit the interests or preferences of individual consumers for products, either explicitly or implicitly, and make recommendations accordingly” (p. 137). These systems acquire insights into user preferences for diverse items, like movies, shopping, tourism, TV programs, and music. Implicit information collection involves the observation of user actions, such as viewed movies, purchased products, or downloaded applications. On the other hand, explicit data gathering entails the collection of ratings from the user (Katarya & Verma, 2017; Lops et al., 2011).

Algorithms have enabled the development and functionality of recommender systems (Möller et al., 2020). These artificial intelligence-based systems operate by evaluating the existing data regarding user behavior patterns and then offering recommendations based on this information (Alyari & Jafari Navimipour, 2018). These recommendations serve the purpose of helping users discover the most fitting options for their needs. The primary objective of recommender systems is to simplify product or service searches, even when limited information about user preferences is available (Caro-Martinez et al., 2018). Indeed, they can be viewed as decision-support tools designed to alleviate the cognitive effort required for processing information within a given choice set (Wang & Benbasat, 2007). These systems effectively mitigate information overload and search complexity, ultimately enhancing decision quality (Häubl & Trifts, 2000; Jannach & Hegelich, 2009). To achieve this, these systems employ a blend of multiple factors to analyze patterns and user attributes, ultimately determining the most suitable product suggestions for customers (Gupta, 2020). This explains why many online retailers have incorporated them into their websites. For example, Amazon, a widely recognized online retailer, effectively employs various types of recommender systems. Once a customer browses or makes a purchase on Amazon, the platform offers personalized suggestions that align with the viewed or purchased item. Additionally, Amazon provides further recommendations in the "customers who bought this item also bought" section, drawing insights from the buying patterns of other customers (Li & Karahanna, 2015). Given the rapid advancements in the realm of artificial intelligence, some scholars believe that recommender systems may surpass human suggestions in terms of accurately aligning with individual consumer preferences (Yeomans et al., 2019). Ricci et al. (2015) mention that a successful recommender system should hold value for both users and e-service providers. Hence, it is crucial to explore methods that enhance the user experience when utilizing recommender systems.

As mentioned by Logg et al. (2019), decision-makers increasingly depend on algorithms for their personal needs, replacing traditional roles with technology. The extensive dependence on algorithmic guidance appears to contrast with findings in the field of judgment and decision-making. Indeed, research has highlighted a prevalent human skepticism toward algorithms, a phenomenon sometimes defined as "algorithm aversion" (Dietvorst et al., 2018; Dietvorst et al., 2015). Nonetheless, the literature presents various reports on the use of algorithmic systems with varied results regarding the inclination to accept and use such systems (Jussupow et al., 2020). Some report that algorithms are preferred over human advice (Logg et al., 2019; Tauchert & Mesbah, 2019). However, others report contradictory results (Castelo et al., 2019; Lee, 2018). Nonetheless, the primary idea centers on consumer preference for humans over algorithms, with some exceptions noted. It is worth noting that algorithms serve as the foundation of recommender systems, relying on them to analyze data and offer recommendations to users (Portugal et al., 2018). Therefore, the insights concerning the acceptance or reluctance toward utilizing algorithms can be applied to the realm of recommender systems.

Multiple studies have supported the claim surrounding algorithmic aversion. Jago (2019) found that individuals perceive algorithms as less authentic compared to humans. Moreover, according to Castelo et al. (2019), people rely less on algorithms for subjective tasks in contrast to objective tasks, in comparison to humans. In the same vein, it has been observed that individuals possess a distorted comprehension of human decision-making, leading to a reluctance to adopt algorithms (Cadario et al., 2021). In addition, it has been demonstrated that trust in medical advice is higher when it comes from a human doctor compared to an algorithm (Longoni et al., 2019; Promberger & Baron, 2006). Similarly, scholars argue that consumers are hesitant to rely on automated medical care because they feel it might not fully consider their unique circumstances, and would rather refer to a human expert (Longoni et al., 2019). Further, Shaffer et al. (2013) discovered that participants viewed physicians who made diagnoses without using an algorithm more favorably than those who employed an algorithm, but equally favorably as physicians who consulted colleagues for assistance in diagnosis.

On the contrary, Tauchert and Mesbah's (2019) study delves into how individuals interact with advice from human advisors compared to financial robo-advisors. Interestingly, participants tended to favor the guidance offered by financial robo-advisors, even when the presentation of the advice was identical. Similarly, Dijkstra and colleagues (1998) discovered that people tend to consider advice from a recommender system to be more logical and impartial when compared to the same advice offered by a human advisor. Logg et al. (2019) found that people conform more to advice when it comes from an algorithm than when it comes from a human advisor. Other findings highlight that consumers tend to prefer algorithm advice over human advice when the utilitarian aspects of a product hold more significance, versus the hedonic aspect (Longoni & Cian, 2022).

These results demonstrate that consumers' attitudes in regards to algorithms differ according to the nature of the task (Castelo et al., 2019), and the specific domain in which the systems are used. Considering the complexity of decision-making, it is not unexpected that various studies have yielded divergent findings. Collectively, these findings imply that the concept of algorithm aversion and advice-taking from various sources is more complex than what earlier research has proposed.

Recommender systems are a subject of extensive research in the literature, and a few key characteristics have been prevalent in RS studies, including explainability. In fact, explanation facilities play a crucial role in enhancing user trust, comprehension, and acceptance of the system (Wang & Benbasat, 2007). Secondly, explainability helps mitigate the "black box" problem, which is prevalent in complex recommendation algorithms (Castelvecchi, 2016). This problem refers to the opaqueness of these algorithms, where it is challenging to discern how and why specific recommendations are made. By providing explanations, recommender systems can make their decision-making processes more transparent and understandable for users, addressing concerns related to algorithmic opacity (Burrell, 2016).

2.3.4.1 Explainability

As AI systems and algorithms become more complicated, a growing number of people view them as “black boxes” that defy comprehension and require specialized knowledge and skill to understand the AI’s decision (Castelvecchi, 2016; Rai, 2020). Explainability provides a solution to this issue by making the RS transparent in the eyes of the user. The class of systems known as explainable AI (XAI) offers insight into how an AI system makes decisions, predicts the future, and takes action (Rai, 2020). According to scholars, “Explainable AI (XAI) refers to artificial intelligence and machine learning techniques that can provide human-understandable justification for their output behavior.” (Ehsan & Riedl, 2020, p. 1) In other terms, XAI refers to AI technologies that provide human-understandable explanations to justify their outputs (Gunning et al., 2019). Indeed, these explanations are considered crucial as they enhance users' confidence in the systems by making their functioning clear and by facilitating the transfer of knowledge to users (Rai, 2020). Consequently, this leads to a more effective utilization of the system and to improved decision-making for the user when selecting products (Gregor & Benbasat, 1999).

There are different ways in which explanations can be presented. An explanation, as opposed to an explainable model, provides the end user with human-understandable reasoning for the AI output, rather than detailing elements pertaining to how the AI models and algorithms work (Ehsan & Riedl, 2020). In this paper, the use of the term explainable AI refers to the AI providing information allowing the user to get a better understanding of the reason behind a decision, as opposed to presenting information about how the decision has been processed (Giboney et al., 2015; Mueller et al., 2019).

Numerous studies have demonstrated that providing explanations supporting a recommendation can effectively influence users' attitudes toward following advice (Adomavicius & Tuzhilin, 2005; Wang & Benbasat, 2007; Ye & Johnson, 1995; Zanker, 2012). When users understand why a recommendation is made, like in the case of XAI, they are better equipped to make informed decisions (Lipton, 2016). In fact, scholars report that explanations can significantly improve users' attitude and global satisfaction with a technological system (Kizilcec, 2016). Explanations are known to increase users' understanding of, as well as the confidence they have in the RS' decisions and recommendations, thereby making the system more useful and acceptable (Ye & Johnson, 1995). In the same line of thought, studies have shown that explaining to the user the reasoning behind a recommendation increased the acceptance of the recommendations (Cramer et al., 2008; Rzepka & Berger, 2018; Sinha & Swearingen, 2002). In addition, transparency in AI recommender systems is vital in managing cognitive effort. Providing explanations for recommendations can enhance user understanding (Tintarev & Masthoff, 2015). When users comprehend why a recommendation is made, they can make more informed decisions with less cognitive effort (Bechwati & Xia, 2003; Bigras et al., 2019). These advantages demonstrate the importance of providing explanations accompanying recommendations from recommender systems. However, other studies have yielded contradictory results. While it is recognized that explanations can enhance the acceptance of recommendations by reducing cognitive effort, there is also evidence suggesting the opposite effect. This is because adding detailed explanations can increase cognitive load as users must process additional information (Burrell, 2016; Gregor, 2001). This heightened cognitive demand can potentially result in diminished decision quality and accuracy. Thus, the relationship between explanations and cognitive effort appears to be complex. Further research is needed to determine the optimal level of explainability in AI systems. Such investigations are essential to find a balance between fostering recommendation acceptance and minimizing cognitive effort.

2.3.5 Convergent and Divergent Recommendations

More and more businesses are adopting a hybrid approach to recommendations, integrating the precision of data-driven algorithms with the perspective of human expertise and experience. For instance, Stitch Fix, an online personal styling service, merges RS advice with advice from fashion experts to offer clothing recommendations to their customers. Additionally, they add a personal touch by including a custom message from a stylist in every delivery (Logg et al., 2019). Similarly, BestBuy, a retailer specializing in tech products and services, offers both RS recommendations and customer reviews on its platform. The famous online retailer Amazon is testing the addition of expert recommendations in combination with its use of RS advice and customer reviews (Xu et al., 2020). Rotten Tomatoes, a movie review website, presents its users with ratings from movie critics and from fellow viewers to guide users in their decision-making.

Combining several recommendation sources has been shown to be highly beneficial. Indeed, according to Xu et al. (2020), integrating multiple sources of recommendation offers notable benefits: It provides consumers with a comprehensive view of their choices, enhancing their understanding of the options available and aiding in decision-making. Additionally, it saves time for customers by eliminating the need to visit multiple external sites to gather advice from different sources. It also offers shoppers a sense of reassurance, as it reduces the risk associated with relying on a single source, which may have an inherent bias toward a specific brand. Moreover, research has shown that combining multiple sources of advice increases accuracy as it reduces the random error associated with each separate advice (Yaniv, 2004).

The convergence of recommendations refers to a scenario where two or more sources provide similar or identical advice or suggestions. In the context of online decision-making, this means that the guidance or product suggestions from different sources, such as RS, experts, or consumer ratings, align with each other. Convergent recommendations can reinforce consumer confidence in a particular choice, as the consistency across sources often suggests a higher reliability or quality of the recommended item (Xu et al., 2020). On the other hand, the divergence of recommendations occurs when two or more sources offer conflicting or differing advice or product suggestions. For instance, a RS might suggest one product based on data, while human experts or consumer reviews might advocate for a different product. This divergence can create a challenging decision-making environment for consumers as they are faced with contradictory information (Xu et al., 2020). When consumers encounter divergent opinions online, such as both favorable and unfavorable recommendations, it can lead to confusion and a tendency to deem the information less credible (Book et al., 2018; Huang et al., 2018; Yang et al., 2012). In the context of decision-making, the presence of varying opinions in online recommendations has been shown to foster a sense of uncertainty (Park & Han, 2008) and may make consumers feel anxious (Vali et al., 2015). An example of this is when a product or service is given both the lowest (1-star) and the highest (5-star) evaluations in a review system; such contradictory feedback can lead to perceptions of inconsistency and doubt (Park & Han, 2008; Siddiqi et al., 2020).

Going back to the example of Rotten Tomatoes, the website presents both recommendations simultaneously to its users. In some cases, the recommendations from both sources align, as it is the case for the movie *Barbie* for which movie critics and the audience attributed the positive scores of 88% and 83% respectively. In other cases, the recommendation score given by movie critics and the one attributed by the audience yield very different conclusions. For instance, for the movie *Aquaman and the Lost Kingdom*, movie critics (labeled Tomatometer), which can be qualified as experts, gave a score of 35% whereas the audience gave a score of 81%. Figure 2.1 demonstrates these examples. Another example could be the use of AI to provide financial recommendations in the field of robo-advisory. Robo-advisors use algorithms to automate investment decisions and tasks traditionally done by human advisors. They merge customer information, like financial goals and risk tolerances, with appropriate asset allocations, and perform actions like portfolio rebalancing and tax-loss harvesting. Companies like Betterment, SigFig, Wealthfront, and Fidelity have incorporated AI into their robo-advisory services (Forbes, 2020). In contrast, a human financial advisor or investment expert might provide recommendations that deviate from those of the AI system. The expert's advice could be influenced by recent market trends, personal experience, or a more nuanced understanding of an individual's financial situation and goals. For example, during a period of market volatility, an expert might recommend a more conservative approach than the AI, which is following its programmed investment strategy. In this scenario, users of platforms employing robo-advisors have access to both AI-generated advice and, if they choose, the insights of human financial advisors. This can sometimes lead to situations where the AI suggests one investment strategy while the human expert recommends another. This reflects the different approaches and interpretations of financial data between algorithmic and human analysis. Previous studies on online reviews and recommendations mainly focused on the effect of the number of recommendations and their valence (Maslowska et al., 2017; Purnawirawan et al., 2012; Zhao et al., 2015). However, little research has explored the influence of conflicting recommendations (Purnawirawan et al., 2012). This raises the question of how users interpret and use this information in cases where these recommendations point in opposite directions. It is essential to investigate how users respond to simultaneous advice from multiple sources and which guidance they prefer, as the collective effects of these recommendations are not yet fully understood. The concept of cognitive dissonance, first introduced by Leon Festinger in 1957, is fundamental to understanding the psychological conflict that arises from encountering divergent recommendations. When individuals are presented with recommendations that are at odds with each other —like in the example in Figure 2.1— they may experience cognitive dissonance. This psychological phenomenon occurs when there is an inconsistency between two cognitions or between a person's beliefs and their actions, leading to a state of mental discomfort (Festinger, 1957).

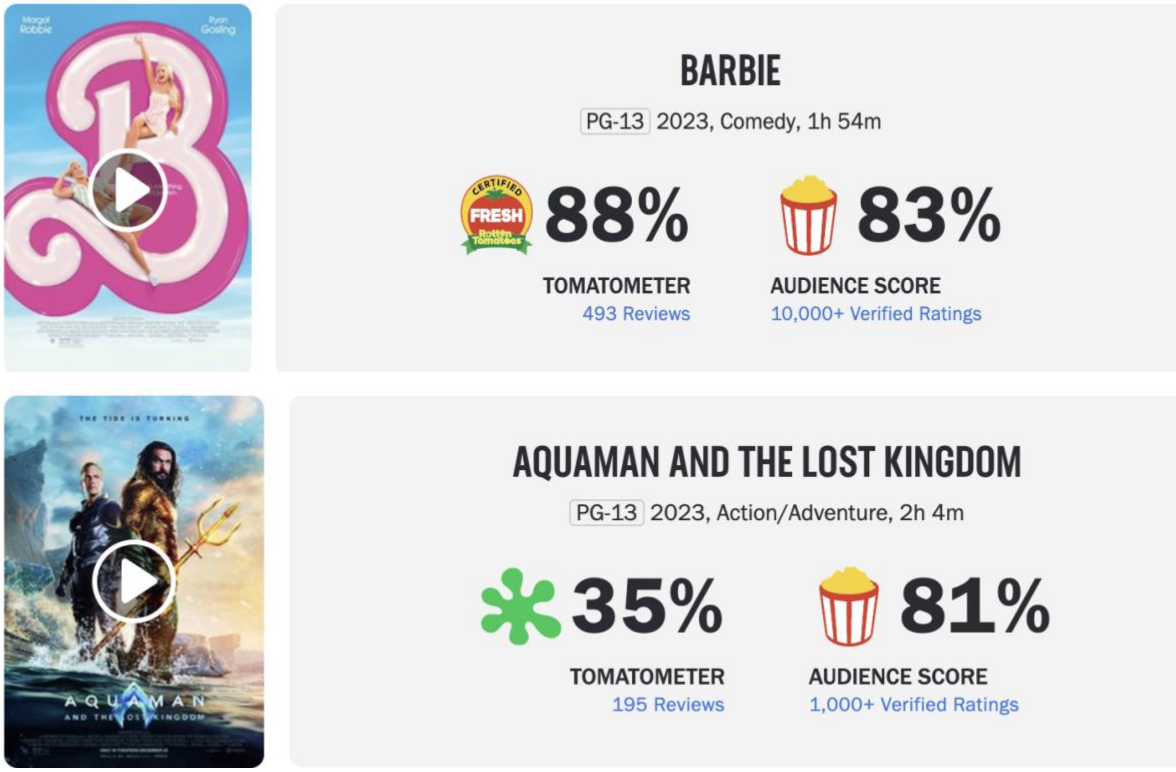

Figure 2.1 Scores of Recommendation Attributed by Audience and Experts on *Rotten Tomatoes*

2.3.5.1 Cognitive Dissonance and Conformity

Building on Festinger's (1957) cognitive dissonance theory, this concept is pivotal in understanding the psychological mechanisms that underpin conformity. Cognitive dissonance occurs when an individual experiences a conflict between their beliefs, behaviors, or attitudes, leading to psychological tension. To resolve this tension and reduce dissonance, individuals may adapt their perceptions, attitudes, or behaviors. This dynamic is not merely a cognitive process but also an affective one, where the emotional discomfort that arises from dissonance can manifest as stress and anxiety (Elliot & Devine, 1994), thereby motivating a change in attitudes or beliefs.

Within environments that offer inputs from recommender systems and experts, individuals are presented with different forms of knowledge: Their own preferences, suggestions from the RS, and advice from experts (Pfeiffer & Benbasat, 2012). When these sources offer conflicting recommendations, the ensuing dissonance can cause significant emotional turmoil. This discomfort is not static; rather, it is part of a fluid process where individuals are inclined to alleviate this distress by adjusting their preferences, a concept known as the construction of preferences (Bettman et al., 1998).

In efforts to achieve consonance, individuals might modify their personal preferences or selectively disregard conflicting information. For example, faced with advice from an expert that contradicts their own preferences, a user might choose to change their stance or ignore the expert's advice (Pfeiffer & Benbasat, 2012). This adaptability in preference formation is crucial in decision-making contexts where dissonance acts as a motivator for change (Harmon-Jones et al., 2009). Further, the research by Van Veen et al. (2009) employed neuroimaging to reveal that cognitive dissonance leads to heightened activity in the dorsal anterior cingulate cortex and the anterior insula—regions of the brain that Aben et al. (2020) also identified as being associated with cognitive effort. This suggests a neurological overlap between the experiences of cognitive dissonance and the exertion of cognitive effort.

The experience of cognitive dissonance is inherently emotional, characterized by feelings of unease, tension, and distress, and when individuals are confronted with divergent recommendations, the resulting dissonance can lead to a significant emotional response (Harmon-Jones et al., 2009). In situations where individuals are faced with contrasting recommendations, the emotional distress associated with cognitive dissonance can influence the extent to which they conform to a majority opinion or authoritative advice. The emotional component of dissonance is thus a significant factor in the conformity process, as individuals seek to reduce negative feelings and restore emotional balance, influencing the extent and direction of conformity behaviors (Cooper & Fazio, 1984).

Therefore, Festinger's (1957) hypothesis suggests that the drive to reduce emotional discomfort can lead individuals to conform to one recommendation over another, highlighting the connected nature of cognitive dissonance, emotional states, and the mechanism of conformity. This adaptation represents the construction of preferences paradigm, which suggests that decisions are not fixed but are susceptible to change under emotional pressure (Bettman et al., 1998). Hence, the experience of dissonance and its accompanying emotional weight is a critical factor in understanding the mechanisms behind conformity.

2.3.6 Expert Recommendations vs. AI Recommender Systems

Scholars have highlighted the importance of recommendation sources on the way the message receiver will perceive the message (Xu et al., 2020). Indeed, as stated by Xu et al. (2020) previous research has expanded understanding of the impacts of different recommendation sources (Benlian et al., 2012; Senecal & Nantel, 2004; Wang & Doong, 2010; Wang et al., 2018; Xu et al., 2017, 2018; Xu et al., 2014). However, participants in these studies were typically exposed to a single source on a website, and only a limited number of studies have investigated the combined influence of two recommendation sources presented simultaneously to the user. As mentioned, combining multiple sources of advice on a website provides many advantages. Despite these clear benefits, to the researchers' knowledge, only two studies have explored the impact of simultaneous presentation of joint recommendations from both recommender systems and human experts in online settings.

Önkal et al. (2009) conducted a study involving financial forecasting. In their study, when presented with advice from a single source, people tended to give more weight to the guidance when they believed it came from a human expert, even if various attributes of human and statistical advice, such as the method of delivery and the chance for interaction, had been standardized, making both forms of advice identical. Furthermore, when participants were simultaneously exposed to two sources of advice, with one source being perceived as a human expert and the other as a statistical method (i.e., recommender system), significantly more emphasis was placed on the advice from the expert source. They report that this inclination persists even in domains where there is no clear evidence that experts' predictions are more accurate than random chance.

Xu et al. (2020) conducted a study focusing on determining the combination of recommendations from various sources (consumers, experts, and RS) that led to the highest acceptance rate. They utilized and expanded the product uncertainty model (Hong & Pavlou, 2014) to explain how the convergence of recommendations from diverse sources impacts customers' acceptance of recommendations. Their experiments revealed that when recommendations align between recommender systems and experts, there is a higher acceptance rate for jointly recommended products compared to scenarios involving experts and consumers or RS and consumers. They explain that this finding is supported by the fact that recommender systems enable the reduction of fit uncertainty, while experts succeed in diminishing description and performance uncertainties. Hence, the collaboration between experts and RS addresses all three dimensions of product uncertainty, thus increasing recommendation acceptance.

Yet, their study does not delve into scenarios where recommendations from recommender systems and experts offer conflicting or divergent recommendations. Hence, there is a gap in the literature concerning the exploration of situations where recommendations provided by recommender systems and experts diverge or present conflicting advice. This gap in the literature represents the need for more focused research of how the convergence or divergence of these recommendations influence the overall user experience and decision-making process. Managers can leverage insights from how users respond to different recommendation sources to tailor the user experience.

2.4 Conclusion

This literature review delves into online recommendation, examining the key factors that influence how users follow or reject the advice given. As decision-support tools become more common on web platforms, it is increasingly important to understand how users emotionally and cognitively process this advice and how it affects their behavior. This understanding is important not just for academic purposes, but it also has practical implications for managers looking to improve user engagement and use these systems to boost business performance. A few research gaps and avenues for future research are identified. A notable research gap exists in how users respond to advice presented simultaneously from two sources—AI-based recommendation systems and human expert opinions—in digital environments. Additionally, there is limited insight into user behavior when confronted with conflicting advice from these sources. The process through which users assimilate and reconcile such contradictory recommendations remains underexplored. Furthermore, existing literature presents inconsistent findings regarding preferences for AI versus human advice, indicating a context-dependent decision-making process. Moreover, there exists an unresolved question of the optimal level of explainability in AI systems, especially concerning how it impacts cognitive load and user comprehension. Studies have yielded contradictory results regarding explanability's impact on cognitive load. Addressing these gaps is important for developing more effective online recommendations and enhancing the quality of user decisions in digital contexts.

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Chapter 3: Empirical Article

Assessing the Influence of Dual-Source Recommendation Characteristics and the Mediating Effect of Cognitive Load and Emotion on Adoption

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Abstract

With the vast amount of information available online, many businesses have started to integrate recommendations into their platforms. These recommendations often originate from two distinct sources: artificial intelligence (AI) recommendation systems and experts. This study investigates how different characteristics of recommendations influence user adoption when AI-based systems and experts offer simultaneous recommendations. It focuses on understanding the roles of recommendation convergence, source indication, and explainability in shaping user acceptance of these recommendations. Furthermore, the study explores the mediating effects of cognitive load and emotional state on the adoption of these recommendations, framed within the stimulus-organism-response model. In a laboratory setting, the research employs a within-subjects design (N=30) to assess the impacts of various recommendation characteristics on users' cognitive, emotional, and behavioral responses. Participants interacted with a simulated movie streaming platform, experiencing simultaneous recommendations from the two sources. Results affirm the significant role of recommendation explainability in user adoption and a preference for convergent over divergent recommendations. Additionally, both source labels and convergent recommendations affect cognitive load and emotional responses. Lastly, an increase in cognitive load is associated with lower adoption of recommendations. This study enhances understanding of interactions with dual-source recommender systems and highlights future research directions.

Keywords: recommender systems, e-commerce, emotion, cognitive load, explainability, convergence, recommendation adoption, recommendation sources, expert advice, source indication

3.1 Introduction

E-commerce continues to grow, offering a vast array of product options to online shoppers. In 2023, worldwide sales from retail e-commerce were estimated to be around 5.8 trillion U.S. dollars (Statista, 2024). It is forecasted that these figures will see a growth of 39 percent in the upcoming years, with predictions suggesting they will exceed 8 trillion dollars by 2027 (Statista, 2024). As of 2023, e-commerce represents about 19.4% of global retail sales, with this share projected to increase steadily, reaching 22.6% by 2027 (Statista, 2024). By 2028, global online retail penetration is expected to rise further to 23.7% (Forrester, 2024). In some regions, such as China and South Korea, e-commerce is anticipated to account for over 40% of total retail sales by 2028 (Forrester, 2024). Amidst this growth, consumers are often overwhelmed by the vast array of choices available, leading to a phenomenon known as choice overload (Manolică et al., 2021). To help customers navigate this abundance and make informed decisions, websites are increasingly incorporating recommendations from various sources. These sources aim to assist customers in their decision-making process and facilitate the selection of the most appropriate item from a multitude of choices (Fayyaz et al., 2020). Online recommendations come from several sources, including other consumers (Chen & Xie, 2008; Yi et al., 2019), product experts (Wang & Doong, 2010), and AI-based recommender systems (Abumalloh et al., 2020; Benbasat et al., 2020; Bigras et al., 2019; Ghasemaghaei, 2020; Xiao & Benbasat, 2014; Xu et al., 2020). Recommendations have proven to be essential to the success of online retailers. Indeed, according to Forbes (2020), 91% of customers are more inclined to purchase products from brands that offer personalized recommendations. In a similar vein, they report that recommendations for products in online shopping carts have persuaded 92% of online customers to make a purchase (Forbes, 2020). Further, Netflix represents another great example of the importance of recommendations, where these recommendations influence 80% of viewership (Chhabra, 2017). These numbers demonstrate the influence of online recommendations in the current digital landscape.

Past research indicates that the origin of a recommendation plays a pivotal role, often exerting a greater effect on how the recipient perceives the message than the content of the message itself.

(Metzger et al., 2010). Numerous studies have enhanced the understanding of the impact different sources of recommendations have (Benlian et al., 2012; Senecal & Nantel, 2004; Wang & Doong, 2010; Wang & Benbasat, 2016; Wang et al., 2018; Xu et al., 2017, 2018; Xu et al., 2014). However, these studies typically involve subjects being exposed to only one source of recommendation on a website, leaving a gap in research regarding the effects of simultaneous recommendations from multiple sources (Xu et al., 2020).

Increasingly, businesses are incorporating diverse recommendation sources into their services. Businesses like Stitch Fix, BestBuy, and Amazon are increasingly leveraging a mix of algorithmic and expert recommendations to enhance customer experiences, providing a blend of data-driven guidance and human insight (Xu et al., 2020). Goodreads, a renowned book recommendation site, combines algorithmic suggestions based on user preferences with community reviews and ratings. Similarly, Netflix employs a recommendation system combined with expert advice, presenting viewers with both algorithm-based suggestions and curated lists like "Netflix Originals". This approach provides many benefits as it significantly enhances the shopping experience by giving consumers a good perspective on their options, streamlining decision-making, and saving time that would otherwise be spent seeking advice from various websites. This approach also instills confidence in consumers by mitigating the risks associated with single-source bias (Xu et al., 2020). Yet, the impact of combining different recommendation sources has yet to be fully explored. Given that websites can easily offer multiple sources of recommendations, researchers should examine scenarios where users encounter a variety of sources at once. Another pertinent issue to consider is the impact of receiving contradictory recommendations, which can occur frequently across various platforms. In the realm of online recommendations, contrasting opinions are common. For instance, Rotten Tomatoes provides film ratings that can show a contradiction between critic scores and audience ratings, reflecting divergent views. In some cases, these recommendations align, as seen with the movie *Barbie*, where both critics and audiences gave positive scores of 88% and 83%, respectively. However, in other instances, the scores differ significantly. For example, *Aquaman and the Lost Kingdom* received a 35% rating from movie critics (the Tomatometer), who are considered experts, while the audience gave it a much higher score of 81%. Figure 3.2 illustrates these examples. In financial services, AI-driven robo-advisors from companies like Betterment and Wealthfront provide automated investment advice, which can differ from the personalized strategies offered by human financial advisors who account for market dynamics and individual profiles. For fashion, services like Stitch Fix use AI to suggest apparel based on user preferences, but these can differ from the advice of human stylists who consider wider trends and direct customer interactions. As receiving conflicting advice is quite prevalent, it is essential to understand consumer behavior and decision-making when faced with such divergent recommendations and how this overlap of information affects users' willingness to follow such recommendations (Xu et al., 2020).

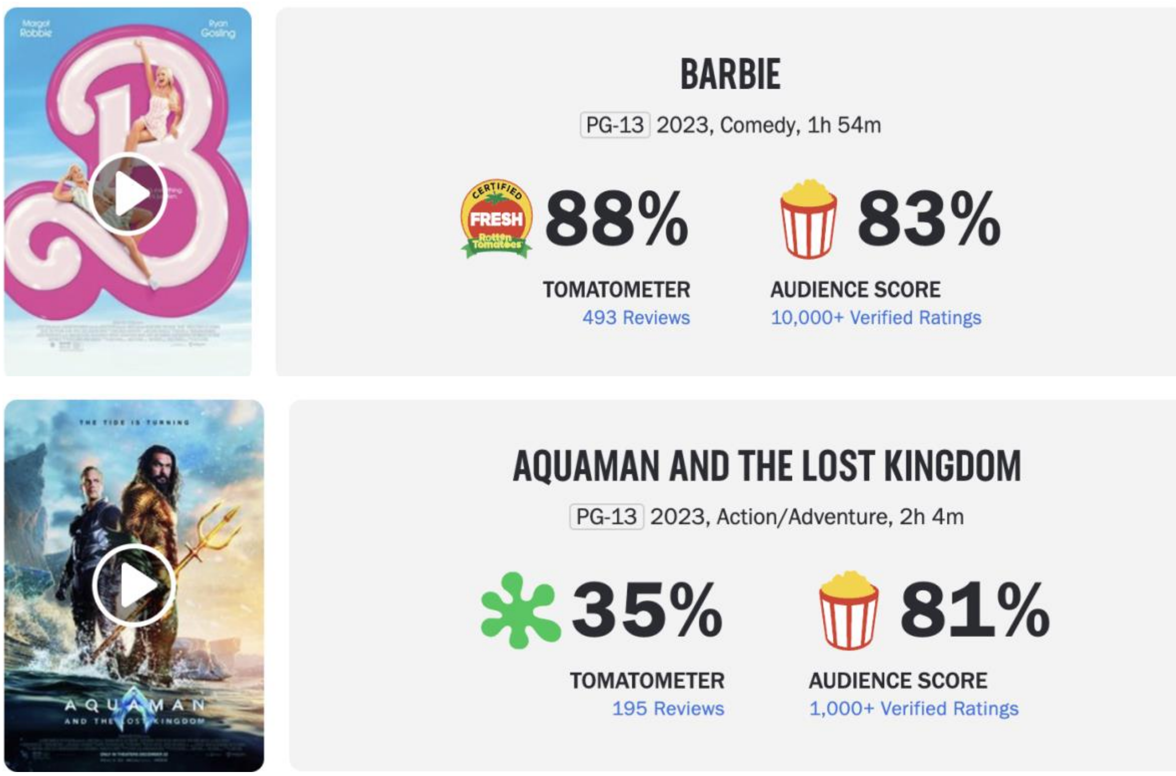

Figure 3.2 Scores of Recommendation Attributed by Audience and Experts on *Rotten Tomatoes*

Extant literature has yielded contradictory conclusions regarding users’ preference for AI advice versus human advice. Some studies suggest a preference for algorithmic advice over human advice (Logg et al., 2019; Mesbah et al., 2021). On the other hand, other studies seem to offer opposing viewpoints (Castelo et al., 2019; Lee, 2018). This discrepancy highlights a research gap, underlining the need to further examine how users might respond when faced with both human and algorithmic advice simultaneously. Research on user reactions to simultaneous recommendations from various sources is limited. To date, only a handful of studies, specifically two known to the researchers, have delved into this area. Xu et al. (2020) research explored the optimal mix of recommendations from different sources like consumers, experts, and AI recommendation systems for maximum acceptance. Building on Hong & Pavlou (2014) product uncertainty model, they found that recommendations from AI-based RS and experts together yield higher acceptance, as they collectively reduce fit, description, and performance uncertainties more effectively than other source combinations. Another study by Önkal et al. (2009) discovered that when presented with both sources simultaneously, people preferred advice from human experts over identical advice from AI-based systems, even when there is no proof that human forecasts are more reliable. Yet, their study does not delve into scenarios where recommendations from AI RS and experts offer conflicting or divergent recommendations. Hence, there is a gap in the literature concerning the exploration of situations where recommendations provided by recommender systems and experts diverge or present conflicting advice.

In addition, previous research has investigated the impact of explainability (Cramer et al., 2008; Kizilcec, 2016; Lipton, 2016; Rzepka & Berger, 2018; Sinha & Swearingen, 2002), and the display of a source label (Ismagilova et al., 2020; Lis, 2013) on recommendation adoption. However, this research primarily focuses on single-source recommendations, leaving a gap in understanding how users respond to these characteristics in joint recommendations, particularly when these sources either converge or diverge in their advice.

Through an experiment, this study aims to assess the impact of specific recommendation characteristics on user adoption when users are provided with simultaneous recommendations from AI-based RS and experts. It will particularly focus on the degree to which recommendation convergence, the presence of source indication, and the level of explainability affect users' acceptance of the suggestions made by these sources. Furthermore, researchers have underscored the significant influence that emotions have on making decisions online, with numerous studies delving into this area (Indiani & Fahik, 2020; Kim & Lennon, 2013; Makkonen et al., 2019; Sahi, 2015; Wu et al., 2014; Yigit et al., 2022). Additionally, the effects of cognitive load on decision-making have been examined, providing insights into how information processing can affect consumer choices (Aljukhadar et al., 2012; Bettman et al., 1990; Pocheptsova et al., 2009). Using the stimulus-organism-response (S-O-R) model (Mehrabian & Russell, 1974), the researchers aim to investigate the mediating effect of these physiological aspects on recommendation adoption when presented with two sources of recommendations simultaneously. To the best of the researchers' knowledge, no study has examined these elements combined. More precisely, the researchers aim to answer the following research questions: To what extent do the characteristics of recommendations influence their adoption when users receive simultaneous recommendations from AI-based systems and human experts? Specific areas of focus include the convergence of recommendations, the presence of a source indication, and the level of explainability offered. Additionally, an exploration is conducted to identify whether there are mediating mechanisms through which physiological factors, such as cognitive load and emotional state, influence the relationship between recommendation characteristics and the adoption of the recommendation by the user. Specifically, this study seeks to elucidate how the cognitive load imposed by recommendation characteristics affects the adoption of the recommendation, and how the emotional state (valence and arousal) resulting from these characteristics impacts user adoption of the recommendations received.

This research makes key contributions to the literature. From a theoretical standpoint, this study fills a gap in the literature regarding how users behave when presented with two sources of recommendations and how different characteristics of these recommendations affect the adoption of advice. Findings highlight a strong preference for convergent recommendations, where advice from AI and experts aligns, significantly enhancing recommendation adoption rates. Furthermore, recommendations that feature high levels of explainability are shown to significantly increase adoption rates. The study also demonstrates that source labels on recommendations increase cognitive load. Also, cognitive load was found to decrease when recommendations converged, but increased when they diverged. Contrary to previous studies, increased cognitive load was found to decrease the likelihood of recommendation adoption. Moreover, convergent recommendations resulted in lower emotional responses. The presence of source labels, however, was shown to cause a more negative emotional valence.

With the growth of e-commerce and the trend of integrating multiple recommendation sources into platforms, this study provides valuable insights for business managers and decision-makers. The findings suggest a user preference for recommendations that align AI advice with human expertise, highlighting the importance of combining both sources to enhance adoption rates. E-tailers should employ a multi-source strategy to boost consumer confidence and simplify decision-making. Additionally, the importance of transparency and explainability in AI systems is emphasized, as understandable recommendations can provide a competitive advantage. Managers are advised to prioritize building transparent systems that clarify the mechanics behind AI recommendations. Lastly, managers should ensure that interfaces are user-friendly and facilitate easy navigation while maintaining the integrity of the recommendation process.

This paper is organized as follows. It starts with a literature review of the main concepts accompanied by a justification of the hypotheses, followed by the presentation of the proposed research model. Next, the methodology of this study is elaborated. The results are then presented, followed by a discussion of the contributions and implications for researchers and management. Finally, limitations and avenues for future research are discussed.

3.2. Literature Review and Hypotheses

3.2.1 S-O-R Model

Mehrabian and Russel (1974) introduced the stimulus-organism-response (S-O-R) model which is a structured framework that systematically explains how an individual's cognitive and emotional states respond to external factors in their environment (Guo et al., 2022; Hussain et al., 2023). In essence, the S-O-R model elucidates the relationship between stimuli (external factors), organisms (comprising an individual's cognitive and emotional aspects), and the resulting response, typically exhibited as behavior. Stimuli (S) represent external inputs from the environment. Organisms (O) encompass the emotional and cognitive aspects that respond to these stimuli in individuals (Eroglu et al., 2003). Response (R) pertains to the actions and reactions individuals exhibit in response to the stimuli (Buxbaum, 2016). Mehrabian and Russell (1974) have proposed that the response component of the model will be characterized with either approach or avoidance actions. In short, in the S-O-R model, the organism is described as the emotional and mental intermediate states and activities that act as a bridge between the initial stimulus and the eventual reaction (Kim & Lennon, 2013; Zhang et al., 2021).

In the context of using technology products, like online recommendations, stimuli refer to a user's perceptions of various product attributes, including design, performance, and the information they obtain while using them. These stimuli play a crucial role in influencing the consumer decision-making process when it comes to technology products (Lee et al., 2011). In the realm of e-commerce, the suggested theory indicates that customers display either approach or avoidance actions based on their impression of the virtual retail space, influenced by their cognitive and emotional state. For instance, if the information provided by an e-commerce site either aids or hinders a shopper's purchasing objectives, it is anticipated that the shopper will show either positive or negative reactions to that specific website, respectively. Signs of approach behavior include the amount of time spent browsing the site, frequent visits, more money spent, and the willingness to continue browsing what the site has to offer. Conversely, avoidance behavior would manifest as the reverse of these actions (Eroglu et al., 2001).

Applying the S-O-R model to the context of online recommendations, this study proposes the stimuli to be reflected by the different attributes of the recommendations (S) presented to the user. These attributes constitute the independent variables under investigation in this study, which include the convergence or divergence of the presented recommendations, and the presence or absence of a source indication and the degree of recommendation explainability.

Combined, these activate the internal states of users (Organism), which in turn, influence users' subsequent behaviors, such as their adoption of the recommended option (Response). The two key aspects of internal states in this context are: (1) users' cognitive state, including cognitive load (2) their emotional state, including valence and arousal (Lee et al., 2011).

The S-O-R model was chosen as the theoretical foundation for this study as this framework has been effectively utilized across various tangible scenarios including retail, services, and consumer behavior (Jacoby, 2002), and extends to digital spaces (Eroglu et al., 2001; Fang, 2012). Multiple studies have employed the S-O-R model to explore consumer behavior in e-commerce settings (Chen et al., 2022; Huang, 2012; Ismail, 2017; Kumar et al., 2021; Peng & Kim, 2014; Yadav & Rahman, 2018; Zhang et al., 2014). Another example includes Jeong et al. (2022) who constructed their research design around the S-O-R framework. They designated both personalized and bestseller recommendations as the stimulus components. It was hypothesized that these stimuli would elicit positive emotional reactions in the organism, that is, the customer, during the purchasing process. The response variable in their model was defined as the customer's action of purchasing the product that was recommended. These prior studies have demonstrated the relevance and applicability of the S-O-R theory in understanding consumers' physiological states and behavioral responses regarding online stimuli.

3.2.2 Cognitive State

Decision making is a complex cognitive process that often involves evaluating various options and information. Cognitive load can be described as the mental resources and processing capacity expended during cognitive tasks, such as problem-solving, learning, and decision-making (Paas et al., 2003). Information overload is a common occurrence due to the inherent limitations of humans when it comes to absorbing and processing information within a given time period (Malhotra, 1982). Especially, the evolution of e-commerce has significantly amplified the challenge of information overload. This term refers to the state where consumers face more information than they can process effectively, impacting their decision-making abilities (Jacoby, 1977). Research has uncovered various factors leading to information overload in the realm of e-commerce. These include an overwhelming array of choices, the complexity of the information provided, the necessity for comparing options, and the presence of contradictory information (Edmunds & Morris, 2000; Li, 2017; Liu & Wei, 2003). In these instances, the consumer can feel overwhelmed by the volume of information, unable to process it effectively. The impact of this overload on consumers is significant, leading to decreased precision in decision-making, longer time taken to make decisions, and increased stress and dissatisfaction, cognitive fatigue and confusion (Bigras et al., 2019; Eppler & Mengis, 2004; Malhotra, 1982; Schommer et al., 2001; Schwartz, 2004).

3.2.3 Emotional State

Studies on emotional affect have generally reached a consensus regarding the fundamental structure of emotional experiences (Feldman, 1995), which is described as a circumplex (Larsen & Diener, 1992; Russell, 1980; Scholsberg, 1941; Watson & Tellegen, 1985). The circumplex model of affect, proposed by Russell (1980), has been a pivotal framework in the study of emotions and affective states. This model visualizes emotions as points in a two-dimensional space defined by two primary dimensions: valence and arousal (Russell, 1980). Understanding these dimensions is essential for comprehending the nature of emotional experiences and their relevance in various domains such as psychology, neuroscience, and consumer behavior.

Valence represents one of the core dimensions of the circumplex model and includes the emotional spectrum of feelings from positive to negative. It pertains to how individuals subjectively assess the pleasantness or unpleasantness of their emotional state (Russell, 1980). Understanding valence is essential as it enables researchers to categorize emotions along the positive-negative continuum, aiding in the interpretation of emotional responses in various contexts (Posner et al., 2005).

The second critical dimension in the circumplex model is arousal, which refers to the degree of physiological activation or energy associated with an emotional state (Russell, 1980). It spans a continuum from low arousal states, such as sleepiness or drowsiness, to high arousal states characterized by alertness, activation, and even frenetic excitement (Russell, 1980; Zimmermann et al., 2006). This dimension provides insights into the intensity of an individual's emotional experience and complements the valence dimension in capturing the richness of emotional responses (Feldman, 1995).

3.2.4 Recommendation Adoption

In the proposed research model of this study, the dependent variable is the reactance behavior to the recommendation, identified as recommendation adoption. This is described as the decision to adhere, conform, adopt, comply with, follow, or accept the recommendation (Aljukhadar et al., 2012).

3.2.5 AI Recommender Systems

Recognizing the challenge of information overload, recommender systems emerge as vital decision-aid tools in e-commerce. Recommender systems are decision-aid tools that can help consumers swift through these sets of choices. In the context of e-commerce, a recommendation system is characterized as an online tool that gathers a consumer’s preferences, either implicitly or explicitly, and suggests personalized products or services from e-tailers accordingly (Li & Karahanna, 2015). Algorithms are at the root of recommender systems, by utilizing data to offer the best suggestions to the user (Alyari & Jafari Navimipour, 2018; Möller et al., 2020). Ultimately the goal of these systems is to help users find the best option for their specific needs. These systems aim to simplify product or service searches, even when limited information about user preferences is available (Caro-Martinez et al., 2018). Further, they help alleviate the cognitive effort required for processing information within a given choice set (Wang & Benbasat, 2007).

3.2.6 Expert Recommendations

Experts provide valuable support in decision-making when an individual lacks the proper knowledge in a particular area (Sniezek & Van Swol, 2001). Bourne et al. (2014) describe an expert as an individual who has attained a significant degree of expertise within a specific area. They characterize expertise as a trait that results from exceptionally high levels of performance in a particular task or field (Bourne et al., 2014). Furthermore, experts are recognized to have the power to persuade decision makers. Persuasion has received considerable attention within the field of social psychology (Gilbert et al., 1998; O'keefe, 2015). Research has focused on examining the influential factors associated with persuasiveness, particularly those related to the person delivering the persuasive message. In this light, high expertise has been shown to be an important factor (Cialdini & Goldstein, 2004; Eagly & Chaiken, 1993; Rhine & Severance, 1970). In fact, it is reported that generally, a message is more persuasive when it is conveyed by an individual with substantial expertise in the subject matter. This influence of experts is founded on the notion that individuals are inclined to place greater trust in the opinions of those believed to have substantial and relevant knowledge (Cartwright & Zander, 1968). Further, the term "expert" inherently suggests a high level of knowledge and experience, thus providing an endorsement for the advice they provide (Önkal et al., 2009). The elaboration likelihood model (Petty & Cacioppo, 1986) provides support as to why individuals may accept expert advice without thoroughly processing the advice (Dijkstra, 1999). The model suggests that individuals tend to form judgments based on peripheral cues when they lack motivation or the ability to critically evaluate the content of a message (Dijkstra et al., 1998). The persuasiveness of the source acts as a peripheral cue and can lead individuals to accept expert advice without questioning the accuracy or relevance of the advice. A common example could be that people may trust a doctor's advice solely because it comes from a medical professional rather than due to an in-depth evaluation of the message's content (Fogg, 2002).

3.2.7 Effect of Recommendations Convergence on Recommendation Adoption

Convergence and divergence in recommendations are two contrasting scenarios that significantly impact consumer decision-making, particularly in online environments. Convergence refers to situations where multiple sources provide similar or identical advice, enhancing consumer confidence in a particular choice. This phenomenon is rooted in the belief that consistency across various sources, such as RS, experts, or consumer ratings, implies higher reliability or quality of the recommended item (Xu et al., 2020). Conversely, divergence occurs when these sources offer conflicting advice, creating a challenging decision-making environment due to the contradictory information presented (Xu et al., 2020). Divergent opinions, such as mixed reviews on products, can lead to confusion, decreased credibility perception, and increased uncertainty and anxiety in consumers (Book et al., 2018; Huang et al., 2018; Park & Han, 2008; Siddiqi et al., 2020; Vali et al., 2015; Yang et al., 2012).

Conformity, a psychological phenomenon where individuals align their opinions and behaviors with a group majority, can be influenced by such convergent or divergent recommendations (Turner, 1991). Social conformity is driven by the desire for social approval, accurate decision-making, and maintaining a positive self-image (Cialdini & Goldstein, 2004; Haun et al., 2013; Morgan & Laland, 2012). Key studies like Asch's conformity experiments reveal that individuals often adjust their views to match the group consensus, even against their personal beliefs, due to the desire for social acceptance or the belief that the majority is correct (Asch, 1956, 2016; Deutsch & Gerard, 1955; Sherif, 1935; Turner, 1991). Hence, it is posited that:

H1: When recommendations from an AI recommendation system and an expert are convergent, users will be more likely to adopt the recommendation.

3.2.8 Source Credibility

Source credibility plays a pivotal role in how individuals perceive and adopt advice, irrespective of whether the advice comes from human experts or computer systems (Cheung et al., 2009; Hovland & Weiss, 1951; Pornpitakpan, 2004). Source credibility is not an intrinsic attribute of a source but is dependent on the receiver's perception of that source (O'keefe, 2015). It is essentially an evaluation of the communicator's believability by the message receiver (Fogg et al., 2002). Studies have consistently shown that people are more likely to be persuaded by sources they perceive as credible, and this credibility often hinges on two primary dimensions: trustworthiness and expertise (Fogg et al., 2002; Petty et al., 1997). Research including Hovland and Weiss (1951) indicates that a source's credibility enhances the credibility of its message.

Thus, by association, an individual who perceives a source to be credible will perceive the message communicated by this source to also be credible. This principle holds true in digital contexts, where credibility significantly influences the acceptance of online recommendations (McKnight & Kacmar, 2006; Sussman & Siegal, 2003), particularly in decision-making like purchases (Nabi & Hendriks, 2003). On the other hand, lower credibility reduces the likelihood of advice being followed, often to mitigate risk (Cheung et al., 2009).

3.2.8.1 Effect of Source Indication on Recommendation Adoption

To effectively aid decision-making, recommendations must come from a source deemed trustworthy by users (Fogg, 2002; Xu, 2014). In environments where customer reviews are available, such as online platforms, individuals often lack any prior personal knowledge of the reviewers whose opinions they are evaluating. Inference theory proposes that individuals rely on accessible cues to form judgments about an unfamiliar source, particularly in the absence of direct experience (Baker et al., 2002). This is especially true in online settings where consumers judge the credibility of recommendations based on available cues within the reviewer's content or profile, assessing expertise and trustworthiness as key factors in their decision-making (Brown et al., 2007; Kirmani & Rao, 2000; Xie et al., 2011; Xu, 2014). Consumers actively seek personal details within reviews that suggest whether the reviewer is an expert or a novice, as this influences their trust in the provided information (Metzger et al., 2010; Smith et al., 2005; Willemsen et al., 2012). Building upon this understanding of trust and credibility, it is important to consider the cognitive mechanisms underlying decision-making in online environments. According to the heuristic-systematic model of information processing, individuals simultaneously engage in two distinct modes of reasoning: heuristic and systematic processing (Chaiken, 1989; Chen & Chaiken, 1999). The decision on which mode to employ is influenced by the sufficiency of heuristic cues in generating confidence in judgments. Koh and Sundar (2007) extend this framework to the domain of media technologies, noting that such technologies can activate either or both types of processing. For example, when a consumer encounters a specialist web agent on a retailer’s website, the presence of heuristic cues like expert recommendations may initially steer them towards heuristic processing. However, if these cues are deemed insufficient for making a confident decision, the consumer will shift to systematic processing (Koh & Sundar, 2007). Indeed, it is a common practice for humans to rely on cognitive heuristics during decision-making processes (Meinert & Krämer, 2022). Heuristics play a pivotal role in simplifying decision-making processes. According to scholars, heuristics are mental shortcuts that facilitate efficient information processing, enabling individuals to make quick, often effective decisions without the exhaustive processing of all available data (Kruglanski & Gigerenzer, 2011; Tversky & Kahneman, 1974). A key heuristic in this context is the expertise heuristic, where decision-makers link expertise with credibility, often activated by cues related to a person's credentials, their field of work, or their titles. These cues are then utilized by the brain as efficient shortcuts, prompting it to classify the individual as an expert and thereby associating expertise to them without a thorough evaluation of the content of the message (Goldstein & Gigerenzer, 2002; Meinert & Krämer, 2022; Metzger & Flanagin, 2007; Taylor & Fiske, 1978). Scholars highlight that emphasizing expertise indicators such as "reviewer of the month" badges or "expert" labels, offers clear and recognizable signs of a source's level of expertise (Ismagilova et al., 2020; Lis, 2013). In turn, this will lead to an increase in the adoption of online product recommendations and enhance purchasing intentions (Ismagilova et al., 2020; Lis, 2013). Thus, the following hypothesis is proposed:

H2: Users will adopt the recommendations from the experts more often when the source indication is displayed than when it is not displayed.

3.2.9 Effect of Explainability on Recommendation Adoption

The impact of source credibility also applies to recommendations from recommender systems (Hyan Yoo & Gretzel, 2008). The first dimension of credibility; trustworthiness, implies that users identify the RS's recommendations as reliable, while the second dimension; expertise, indicates that the system is recognized by users as knowledgeable and capable of providing the right answers (Fogg, 2002; Senecal & Nantel, 2004; Xiao & Benbasat, 2007). Scholars have shown that both dimensions of source credibility are reinforced when the rationale behind recommendations is made transparent (i.e., explainability) (Sinha & Swearingen, 2002). In other words, scholars explain that when users are provided with clear explanations supporting the reasoning behind recommendations, this transparency enhances their trust in the RS and positively influences credibility (Heesacker et al., 1983; Pu & Chen, 2006). Explainability in the context of RS refers to the clarity and understandability of the reasons behind the RS's suggestions. It involves providing users with accessible explanations that make the AI's decision-making process transparent, thereby demystifying the "black box" nature of complex algorithms (Castelvecchi, 2016; Ehsan & Riedl, 2020; Rai, 2020). Explainable AI (XAI) systems offer insights into how AI systems make decisions and predict outcomes, which is crucial for user trust and effective system utilization, thereby improving decision-making (Gregor & Benbasat, 1999; Gunning et al., 2019; Rai, 2020).

When users perceive the RS as trustworthy and as an expert, their intention to adopt the RS's recommendations increases (McKnight & Kacmar, 2006; Xiao & Benbasat, 2007). This perception of credibility, enhanced through explainability, can reduce the cognitive effort required in decision-making, increase satisfaction with the decision process, and ultimately lead to a greater inclination to follow the recommender system's advice (Bechwati & Xia, 2003; Bigras et al., 2019; Cramer et al., 2008; Rzepka & Berger, 2018; Sinha & Swearingen, 2002). Therefore:

H3: Users are expected to adopt recommendations from the AI recommender system more frequently under conditions of high explainability as compared to conditions of low or no explainability.

3.2.10 The Mediating Effect of Cognitive Load on Recommendation Adoption

Research has delved into the impacts of cognitive load on decision-making processes, offering valuable perspectives on the ways in which the processing of information can influence the decisions of consumers (Aljukhadar et al., 2012; Bettman et al., 1990; Pocheptsova et al., 2009).
When experiencing high cognitive load, consumers are known to act as satisficers rather than optimizers (Malhotra, 1982). That is to say that they seek a satisfactory solution rather than the optimal one, often due to cognitive constraints and limited time (Roubal, 2018). Further it is

expected that consumers will use decision heuristics to streamline decision-making when experiencing high cognitive load (Malhotra, 1982). When consumers are overwhelmed with information, they are more likely to exhibit low reactance behavior and tend to agree with and adopt product recommendations, a concept rooted in the adaptive decision-maker model of consumer behavior (Aljukhadar et al., 2012; Bettman et al., 1990). As explained by Aljukhadar et al. (2012), research on self-regulation also supports this phenomenon, suggesting that an overload of information can deplete cognitive resources, thereby amplifying intuitive reasoning at the expense of deliberate and precise processing of product information (Pocheptsova et al., 2009). Relying on intuitive judgment enables consumers to comply more easily with a recommendation rather than re-evaluate and possibly challenge it. Additionally, by conforming with recommendations provided by recommender systems, the consumer is able to keep their cognitive load at a manageable level (Aljukhadar et al., 2012). In the same line of thought, when overwhelmed, users are inclined to use heuristics to simplify information processing, and a RS can be viewed as one such heuristic for streamlining information processing (Aljukhadar et al., 2012; Häubl & Trifts, 2000). Considering that both AI-generated and expert recommendations can be viewed as heuristics, it is anticipated that consumers will tend to accept recommendations when they face high cognitive load.

3.2.10.1 Recommendation Convergence and Cognitive Load

When presented with divergent recommendations, consumers are faced with additional difficulty in their decision-making process resulting from conflicting information (Xu et al., 2020). In settings where individuals receive inputs from AI recommender systems and experts, they encounter a mix of knowledge sources: their own preferences, suggestions from recommender systems, and expert advice (Pfeiffer & Benbasat, 2012). This multifaceted information landscape presents a unique challenge, as individuals may experience cognitive dissonance when balancing their existing attitudes with new information, especially when making product choices. Within the context of decision-making, the cognitive dissonance theory (Festinger, 1957), suggests a framework for understanding how individuals modify their attitudes toward selecting and purchasing products to diminish psychological discomfort (Bettman et al., 1998; Festinger, 1957; Kim & Benbasat, 2013). Cognitive dissonance refers to a psychological discomfort because of inconsistencies between cognitions or between an individual's beliefs and behaviors (Festinger, 1957). When consumers are faced with divergent recommendations from different sources, they may experience a state of cognitive dissonance. Further, neuroimaging studies have demonstrated a neurological basis for cognitive dissonance, with Van Veen et al. (2009) showing increased activity in the dorsal anterior cingulate cortex and the anterior insula, areas that Aben et al. (2020) also associate with cognitive effort. This finding indicates that the experience of cognitive dissonance coincides with increased cognitive effort. Similarly, in their research, Fan (2014) showed that tasks with conflicting information demand more cognitive effort compared to those with congruent information. Thus, when confronted with divergent recommendations, the cognitive effort required to assimilate and reconcile conflicting information is significantly amplified. Hence, given that divergent recommendations increase cognitive load and induce a state of cognitive dissonance, which is likewise linked to heightened cognitive effort, the following is anticipated:

H4a: Divergent recommendations will increase cognitive load, which in turn will serve as a mediator and lead to increased recommendation adoption.

3.2.10.2 Source Indication and Cognitive Load

Consumers tend to look for personal details within reviews that indicate whether the reviewer is an expert or a novice, as this affects the level of trust they place in the information provided (Metzger et al., 2010; Smith et al., 2005; Willemsen et al., 2012). In online decision-making, consumers may initially engage in heuristic processing when influenced by cues such as an "Editor’s Pick" label, which suggests expertise. Should these heuristic cues prove insufficient for a confident purchase decision, consumers may then resort to systematic processing (Koh & Sundar, 2010). This involves a detailed examination of product descriptions and reviews, as well as an analysis of indicators of source credibility to further validate their choice, as discussed by Koh and Sundar (2010). In a context where the only information available to the consumer about the reviewer is the "Editor’s Pick" label, with no additional details such as the reviewer’s content or profile (Brown et al., 2007; Kirmani & Rao, 2000; Xie et al., 2011; Xu, 2014), the expertise cue is likely insufficient to solely trigger heuristic processing, as it does not provide enough to assess the reviewer's expertise. Therefore, the consumer is expected to engage in systematic processing. In fact, the initial expertise cue triggers a dual-processing mechanism, as outlined in the heuristic-systematic model (Chaiken, 1989; Chen & Chaiken, 1999), prompting a more thorough investigation into additional cues. This type of information processing leads to an increase in cognitive effort as consumers seek further data to support the credibility of the recommendation and the authority of the source (Petty & Cacioppo, 1986). In turn, given that a higher cognitive load has been shown to increase the likelihood of accepting recommendations, we propose the following hypothesis:

H4b: The display of the source indication "Editor's pick" will lead to higher cognitive load, acting as a mediator, and leading to higher recommendation adoption.

3.2.10.3 Explainability and Cognitive Load

In addition, transparency in AI recommender systems is vital in managing cognitive effort (Herm, 2023). Providing explanations for recommendations can enhance user understanding (Tintarev & Masthoff, 2015). On the one hand, understanding the rationale behind recommendations enables users to make choices that are more informed and require less cognitive effort (Bechwati & Xia, 2003; Bigras et al., 2019). On the other hand, the explanations provided by the AI RS to justify the rationale behind the recommendation require additional cognitive effort from the user to process the information in the explanations. Indeed, while explanations are often seen as a way to reduce cognitive effort and enhance recommendation acceptance, there is evidence suggesting the opposite effect may occur. When detailed explanations are added, they introduce additional information that the user must process, which can increase cognitive load (Burrell, 2016; Gregor, 2001). In fact, detailed explanations can lead to information overload, potentially impairing users' decision-making abilities (Gregor, 2001). Hence, considering that an increase in cognitive load leads to increased recommendation acceptance, the following hypothesis is proposed:

H4c: Recommendations by an AI recommender system with high explainability will lead to higher cognitive load in the user (when compared to systems with low or no explainability), acting as a mediator and leading to higher recommendation adoption.

3.2.11 The Mediating Effect of Emotional State on Recommendation Adoption

The role of emotion in consumer decision-making has been extensively examined across numerous studies in the academic literature, evidencing a significant impact on consumer choices and behavior (Bagozzi et al., 1999; Lerner et al., 2015). These investigations have consistently highlighted the profound influence that emotional states exert on the decision-making process of consumers (Pham, 2007; Schwarz & Clore, 1983).

The affect-as-information theory posits that emotions serve as a critical informational component in the decision-making and judgment process (Schwarz & Clore, 1983). According to this theory, individuals often rely on their emotional states as a guide for decision-making. For instance, experiencing happiness when engaging with a new product could be translated as a sign of the product's quality, potentially leading to a purchase. Conversely, discomfort or unease during decision-making could be taken as an intuitive warning, prompting an individual to reconsider or even avoid the decision. Essentially, emotions act as signals, providing guidance on how one might react or think in response to their surroundings or various scenarios (Pham, 2007).

The affect-as-information theory is integral to the understanding of consumer behavior in e-commerce, where the immediate emotional reactions of customers to online stores significantly shape their purchasing decisions. Scholars suggest that feelings of pleasure or frustration not only inform but also direct buyers' actions, becoming a heuristic to cope with the overload of choices available online (Pham, 2004). These emotional cues typically steer consumers towards choices that align with their current affective state (Schwarz & Clore, 2007). For instance, positive emotions often lead to a broad, heuristic approach to processing information, encouraging more engagement and interaction with the online platform. This can manifest as extended browsing time and increased likelihood of making a purchase. Conversely, negative emotions can emerge from a mismatch between expectations and actual experiences, such as a complicated checkout process, unclear product descriptions, or unexpected costs, which may provoke frustration or anger (Moors, 2014). This irritation can prompt a more analytical and critical interaction with the site, often causing consumers to perceive the site negatively. Such an analytical approach increases the chance of consumers abandoning their carts and leaving the site prematurely (Xia, 2002). Further, a substantial body of research has consistently demonstrated that the emotions consumers experience at any given moment significantly influence their subsequent behaviors (Chisnall, 1995; Fang, 2014; Herabadi, 2003; Peck & Wiggins, 2006).

This concept aligns with the S-O-R model, which posits that experienced emotions act as mediators between the stimulus and the resulting behavior (Mehrabian & Russell, 1974). Emotions, as experienced by the organism, are not just passive experiences; they actively inform and predict behavioral outcomes. Positive emotions typically lead to an approach behavior, wherein individuals are drawn towards a stimulus, while negative emotions generally result in avoidance behavior, prompting individuals to withdraw from the stimulus (Mehrabian & Russell, 1974). In the current research, the relationship between emotional responses and consumer actions is examined through the lens of the S-O-R model. Fang (2014) provides empirical support for this model by demonstrating that emotions experienced in response to a product recommendation significantly predict consumer behavior (i.e., recommendation adoption). Specifically, their research shows that positive emotions are implicated in driving approach behaviors, which are indicative of a consumer's inclination to adopt a recommendation. In contrast, negative emotions are correlated with avoidance behaviors, leading to a hesitancy to adopt the recommendation. This evidence highlights the critical role of emotions as mediators between stimuli and behavioral outcomes within consumer decision-making processes. Hence, emotional state (valence and arousal) positively influences recommendation adoption.

3.2.11.1 Recommendation Convergence and Emotional State

As mentioned, when presented with divergent recommendations, individuals can experience a state of cognitive dissonance. This state can be characterized by emotional discomfort, manifesting as stress and anxiety (Elliot & Devine, 1994). To alleviate this tension and achieve consonance, individuals may attempt to modify their attitude regarding the source of recommendation or the product, look for convergent recommendations, or disregard the recommendation altogether, a process referred to as the construction of preferences (Bettman et al., 1998; Kim & Benbasat, 2013; Pfeiffer & Benbasat, 2012). In addition, scholars have shown that in an effort to mitigate negative emotions associated with dissonance, individuals are more likely to conform with the majority opinion, which in this case would be convergent recommendations (Cooper & Fazio, 1984; Harmon-Jones et al., 2009).

H5a: Divergent recommendations will lead to a negative emotional state, acting as a mediator, which in turn will lead to lower recommendation adoption.

3.2.11.2 Explainability and Emotional State

Scholars have characterized a condition known as lack of transparency anxiety, which describes the anxiety stemming from the uncertainties that lie in the unknown factors of AI decision-making processes (Li & Huang, 2020). Several problems may emerge from the absence of transparency (i.e., explainability) (Li & Huang, 2020). To begin, failing to add explanations to accompany a recommendation can make it difficult for users to understand the reason why a certain output was made (Castelvecchi, 2016). Another issue is the lack of accountability, making it complicated to identify whether an AI error is due to a fault in the system's logic or a deliberate design choice by its designers (Clarke, 2019). Additionally, when the inner workings of AI are not clear, it becomes challenging to anticipate the system's actions (Clarke, 2019; Li & Huang, 2020). These uncertainties can foster negative emotions among users. Psychologists have recognized that humans inherently experience anxiety or fear stemming from the unknown, particularly when lacking necessary information (Carleton, 2016). Hence, a lack of information allowing the user to understand the reasons behind an AI system's output is believed to lead to such negative emotions. In the same vein, a study by Jhaver et al. (2018) shows that lack of explainability is associated with feelings of loss, frustration, and uncertainty towards algorithms. They found that these negative emotions are reduced upon receiving explanations about the reasoning behind the algorithm's decisions. In turn, these negative emotions can lead to an avoidance behavior in the user (Mehrabian & Russell, 1974). As a result, it is hypothesized:

H5b: Recommendations by an AI recommender system with high explainability will lead to more positive emotions in the user (when compared to systems with low or no explainability), acting as a mediator and leading to increased recommendation adoption.

3.2.12 Proposed Research Model

The research model developed for this study is based on the stimulus-organism-response model (Mehrabian & Russell, 1974), integrating recommendation convergence, source indication, and explainability as stimuli. These factors affect the organism, conceptualized here as the user's cognitive load and emotional state, which ultimately influence the user's response, specifically the adoption of recommendations (see Figure 3.1).

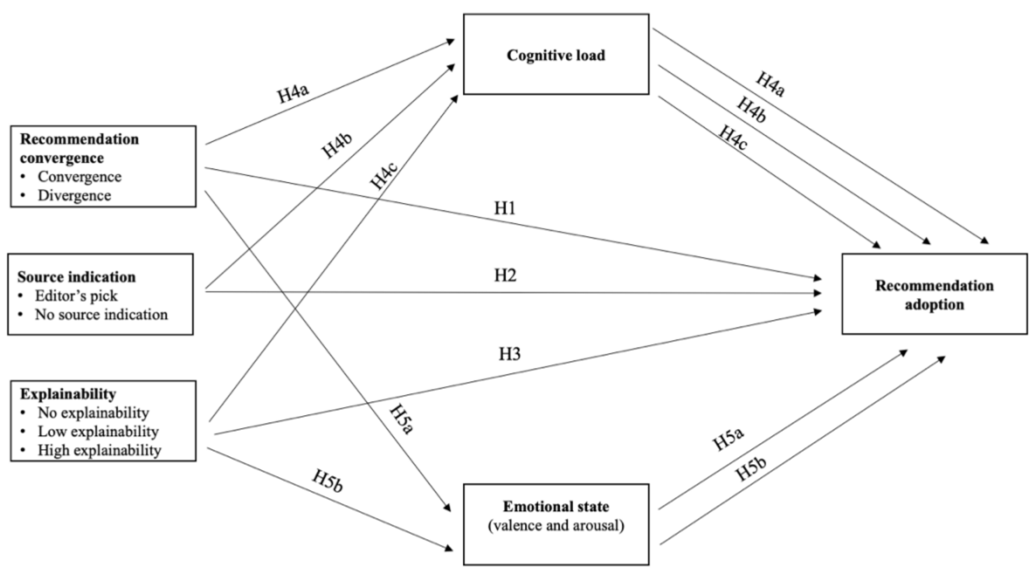

Figure 3.1 Proposed Research Model

3.3 Methodology

3.3.1 Experimental Design

A laboratory experiment was selected as the primary research method for this study due to its ability to control variables and directly observe the effects of specific manipulations on participants' behaviors or responses. The decision to conduct a laboratory experiment was further substantiated by the necessity to collect physiological data from participants which requires a controlled and precise environment to ensure accuracy and reliability. Laboratory settings have the specialized equipment and controlled conditions essential for measuring physiological responses, such as cognitive load and emotional state with minimal external interference, as is the case in this study. The laboratory environment not only facilitated a controlled manipulation of the experimental variables but also ensured that the physiological data collected were reflective of the participants' responses to these specific manipulations, rather than extraneous factors. This experiment received approval from the Ethical Review Board of the researchers' institution, under project number 2023-5114.

The present study employed a 2x3x3 within-subject factorial design to investigate the effects of recommendation source and recommendation attributes on users' physiological states (ie., cognitive load and emotional state) and behavior. The first factor considers the alignment of the recommendation given by the AI recommender system and the one given by experts with two levels: convergent or divergent recommendations. The second factor consists of the source indication presented with the recommendation with two levels: No source indication, and the source indication "Editor's pick". To enhance clarity and coherence in the presentation of this research, uniformity was ensured in the presentation of both expert recommendations and AI-generated recommendations. Although the source indication is inherently specific to expert advice, for the sake of uniformity, AI recommendations were labeled as "Powered by AI". The third factor comprises explainability with three levels: no explainability, low explainability and high explainability. Similarly to the second factor, for the sake of uniformity, even though explainability is typically exclusive to AI recommender systems, an equivalent level of explainability to the expert recommendations was applied to maintain a consistent comparison framework between the two information sources. The levels of explainability were manipulated by adding explanations of varying details. The distinction between low and high explainability in this study was based on a qualitative assessment rather than a quantitative one. Table 3.1 provides examples of the types of explanations provided by each source at each level. The study employed a within-subjects design, comprising twelve conditions and ten trials per condition, for a total of 120 pages of movie stimuli presented to each participant in a randomized order.

Table 3.1 Examples of Explanation Types by Source and Level

	AI advice	Expert advice
No explainability		
Low explainability	Based on your personalized profile.	Based on critics' appreciation.
High explainability	Based on previous choices, including movie plot.	Based on their evaluation of movie plot.

3.3.2 Participants

The study draws from a sample of thirty participants (N=30), with ages between 21 and 60 years old (M_{age}=30.2, SD= 9.1). The participants were recruited via the participant panel of the researchers' institution. The sample comprised 19 females and 11 males. Participants were carefully screened based on specific inclusion and exclusion criteria to ensure eligibility for the study. The inclusion criteria necessitated that participant possessed normal vision and an advanced understanding of both written and spoken English, in addition to being over the age of 18. Conversely, the exclusion criteria were established to disqualify individuals with skin allergies or heart problems, prioritizing the health and safety of the participants throughout the experiment. Further, to take part in this study, each participant signed a consent form which has been approved by the Research Ethics Board of the researchers' institution. As a compensation, participants received a $30 electronic money transfer.

3.3.3 Experimental Procedure

The Wizard of Oz paradigm was used as a strategy for this experiment. This technique often employed in human-computer interaction studies involves participants interacting with a system that they believe to be autonomous; however, it is actually being operated or controlled by an unseen human facilitator (Kelley, 1984). This approach allows researchers to simulate the functionality of technological systems not yet fully developed or too resource-intensive to implement for the study (Nielsen Norman Group, 2022). In the context of this study, (Kelley, 1984) it was selected as a solution to avoid the substantial costs and resources required for the development of a fully functional prototype. Given the scope of this research, creating a real-time, data-driven recommendation engine was deemed unfeasible. This method thus provided a viable alternative as it allowed for the exploration of user experiences and system usability without the necessity of a complete technological system (Nielsen Norman Group, 2022). The experiment was designed to simulate a genuine interaction with a movie streaming and recommendation interface. Participants were led to believe they were engaging with an automated system capable of learning their preferences and making personalized content recommendations. However, unknown to them, a facilitator, referred to as the "wizard", was discreetly managing the system's responses from behind the scenes. The wizard's tasks were multifaceted; initially, as participants created their user profiles, the wizard used a synthetic voice to echo their selections, thereby reinforcing the illusion of system responsiveness. Furthermore, the wizard manually executed actions on behalf of the system, such as highlighting selected elements and navigating through different pages of the interface, in response to participants' inputs. This arrangement ensured a seamless interaction, mimicking the experience of a fully automated website.

In the experiment, participants were informed that they would be evaluating a prototype version of a movie streaming platform. The experiment comprised several steps aimed to elicit a belief in participants that an AI-based system was being trained to personalize recommendations based on their preferences. Procedures began by instructing participants to create an account and provide information about themselves to the AI system. The first task required participants to rate a series of 10 popular movies using a five-star scale, accompanied by an AI-generated voice simulating an actual recommendation system. Subsequently, participants were asked to indicate their preferred movie genres from a provided selection. To further reinforce the illusion of the AI system's functioning, a loading bar was displayed, claiming to show the system's progress from "Analyzing results" to "Matching preferences to movie database" to "Finalizing profile" and ending in the message "Profile ready."

Two trial runs were provided for participants to practice the task, during which any questions or concerns were addressed by the researcher. The choices made during the trial runs were not included in the final analysis. During the actual task, on each trial, participants were presented with a page featuring a movie poster and two recommendations, one from an AI-based recommender system and the other from movie experts. Participants were instructed to make a decision based on the presented recommendations and information, and were provided with two options to choose from by clicking on them, represented by buttons labeled “Add to my watchlist” or “Do not add to my watchlist”. Participants were then allowed to complete the task with no imposed time limit.

To minimize formed attitudes in participants' movie selections, the stimuli comprised mostly unpopular, unknown, or older movies, which were pre-tested with a small number of participants to ensure that they were not overly familiar. Participants were encouraged to make genuine selections, as they were informed they would receive a $10 voucher to the hypothetical streaming platform to watch their chosen movies. This incentive aimed to encourage genuine engagement and increase participants' involvement in the task.

It is important to note that the design of this study included a predetermined and uniform set of recommendations for all participants, contrary to their perception of receiving personalized recommendations. As mentioned, this approach was taken because building a fully functional recommendation system which could tailor recommendations to each participant's preferences, was deemed unfeasible within the scope of this study. Instead, the study opted for a simplified method, where all participants received the same pre-designed set of recommendations, regardless of their individual inputs. The "Wizard of Oz" setup was used to simulate a personalized system, creating the illusion that the system had adapted to each participant's preferences, even though this was not the case. This means that while participants perceived the recommendations as tailored specifically for them, all participants received the same set of recommendations throughout the study. Additionally, the streaming platform and the associated vouchers presented during the experiment were fictitious. The utilization of deception, inherent in studies employing a concealed wizard, necessitates ethical considerations, including the obligation to inform participants of the true nature of the experiment upon its completion (Nielsen Norman Group, 2022). Consequently, during the post-experiment debriefing, participants received clarification regarding the actual objectives of the study and the fictional elements of the system they interacted with. They were informed that the responses they received were not personalized and that the streaming platform was hypothetical. To compensate for the deception, participants were offered an additional monetary compensation of $10, augmenting the initial compensation to a total of $30, instead of the previously mentioned $20 compensation for participation and 10$ voucher.

3.3.4 Measures

Recommendation adoption was evaluated by monitoring participants' actions when clicking the “Add to my watchlist” or “Do not add to my watchlist” buttons. Their responses were recorded—followed the recommendation or did not—and associated these with the specific source of the advice they opted to follow. When recommendations converged, the adherence or non-adherence to these suggestions was tracked. In cases of divergent advice, their responses were linked to the source of the recommendation they chose to adopt.

An integrated multi-system setup was used to collect physiological data. Tobii x60 (Tobii, Stockholm, Sweden) was used for capturing participants' mouse click responses and eye-tracking data, including gaze, and pupil dilation as an indicator of cognitive load (Léger et al., 2019; Léger et al., 2014). To assess the cognitive effort exerted by users in decision-making tasks, the task-evoked pupillary response was analyzed, specifically the average percentage change in pupil diameter from a baseline for each participant and event (Attard-Johnson et al., 2019; Beatty, 1982). This method was preferred over raw pupil size variation to account for differences between participants (Hudon et al., 2021). Facial expressions indicating emotional valence were recorded by Facereader (Noldus, Wageningen, the Netherlands) through a desktop webcam, while arousal levels were measured via phasic electrodermal activity (EDA) using the MP-160 BIOPAC BioNomadix system (BIOPAC Systems Inc., Goleta, CA, USA). Table 3.2 presents a summary of the measures used and their respective operationalization.

Table 3.2 Operational Definitions and Measures Employed in the Study

Construct	**Measure**	**Tool**
Cognitive load	Pupil dilation	Tobii x60
Emotional arousal	Phasic electrodermal activity (EDA)	MP-150 Biopac BioNomadix system
Emotional valence	Facial expressions Valence Score: Ranges from -1 to +1, computed by subtracting the intensity of the most pronounced negative emotion (Angry, Sad, Disgusted, Scared) from the intensity of Happy.	Facereader
Recommendation adoption	Mouse click	Tobii x60

3.3.5 Statistical Analysis

Descriptive analyses and regression modeling were conducted using SAS version 9.4 (SAS Institute Inc., Cary, NC, USA), while mediation analyses employed R version 4.3.2 (R Core Team, R Foundation for Statistical Computing, Vienna, Austria) with the "mediation" package at

1000 simulations (Imai, Keele, Tingley, et al., 2010). Logistic regression with a random intercept model was employed to investigate the effect of the three independent variables—convergence of recommendations, presence of source indication, and level of explainability—on the dependent variable, recommendation adoption. The Wald test was also employed for a global assessment of the relationship between recommendation adoption and the three independent variables, while a Type III ANOVA was utilized for the analysis of repeated measures. Logistic regression with a random intercept model was also used to perform a pairwise comparison among the three levels of explainability (none, low, and high) to discern their impact on recommendation adoption. The mediation analysis utilized a logistic regression with a random intercept model to assess how cognitive load and emotional affect mediated the effects of three independent variables on the dependent variable, recommendation adoption (Imai, Keele, & Tingley, 2010; Imai et al., 2011; Imai, Keele, & Yamamoto, 2010; Imai & Yamamoto, 2013). All statistical analyses were performed separately for each independent variable to isolate and assess their individual effects on the dependent variable. Significance was determined at $p < 0.05$.

3.4 Results

3.4.1 Descriptive Statistics

For the first independent variable, recommendation convergence, the mean emotional valence score in the divergent condition was slightly negative (M = -0.045, SD = 0.093), indicating a general tendency towards less favorable emotional reactions. Comparatively, the convergent condition showed a mean emotional valence that was also slightly negative (M = -0.044, SD = 0.094), suggesting a marginal difference between the conditions in the average emotional response. The arousal levels, as indicated by phasic skin conductance, revealed higher arousal in the convergent condition (M = 0.099, SD = 0.498) compared to the divergent condition (M = 0.088, SD = 0.361). This suggests that convergent recommendations are associated with a slightly higher emotional engagement. Cognitive load, as measured by pupil dilation, showed a negligible difference between the divergent (M = -0.218, SD = 0.223) and convergent conditions

(M = -0.217, SD = 0.222). This similarity implies that the type of recommendation, whether convergent or divergent, did not substantially impact cognitive load. Finally, the rate of recommendation adoption was significantly higher in the convergent condition (M = 69.34%, SD = 0.461) compared to the divergent condition (M = 32.45%, SD = 0.468). This indicates a marked tendency to adopt recommendations when they are convergent.

For the second independent variable of source indication, the mean emotional valence was marginally more negative when the source was indicated (M = -0.048, SD = 0.090) as opposed to when it was not indicated (M = -0.041, SD = 0.097). This minor difference suggests that the participants' emotional response was relatively stable, irrespective of source indication. The arousal levels were higher in the presence of a source (M = 0.095, SD = 0.445) compared to its absence (M = 0.093, SD = 0.448), pointing to a slightly increased emotional engagement when sources were identified. Regarding cognitive load, there was little variation between the two conditions. With source indication, the mean pupil dilation stood at (M = -0.211, SD = 0.220), and without it, the mean was (M = -0.223, SD = 0.226), suggesting that the presence or absence of source indication had a negligible effect on cognitive load. The adoption of recommendations did not display a noticeable difference when the source was indicated (54.57%, SD = 0,498) compared to when it was not (54.78%, SD = 0,497).

Lastly for the independent variable of explainability, emotional valence, which was consistently negative across all conditions, showed little variation, suggesting that explainability did not significantly affect the participants' emotional valence. Similarly, arousal levels also did not demonstrate a consistent pattern concerning explainability levels, which indicates that emotional engagement might be independent of how much the recommendations are explained. Cognitive load remained relatively consistent regardless of the level of explainability, suggesting that the cognitive demand required to process the information was similar across all conditions. This uniformity across the no explainability (M = -0.210, SD = 0.226), low explainability (M = -0.223, SD = 0.219), and high explainability conditions (M = -0.221, SD = 0.222) indicates that participants' cognitive effort was not significantly altered by the degree of explainability. Lastly, the adoption of recommendations was positively correlated with the level of explainability. The adoption rate was highest in the high explainability condition (M = 60.27%, SD = 0,489), followed by the low explainability condition (M = 56.56%, SD = 0,495), and was lowest when no explainability was provided (M = 47.84%, SD = 0,499). These rates suggest that greater explainability is associated with an increased likelihood of recommendation adoption. Table 3.3 highlights the descriptive statistics for each recommendation characteristic.

Table 3.3 Descriptive Statistics for Each Recommendation Characteristic

		Emotional Valence		Emotional Arousal		Cognitive Load		Recommendation Adoption	
		M	SD	M	SD	M	SD	M	SD
Recommendation Convergence	Divergent	-0.045	0.093	0.088	0.361	-0.218	0.223	32.45%	0.468
	Convergent	-0.044	0.094	0.099	0.498	-0.217	0.222	69.34%	0.461
Source Indication	Not Indicated	-0.041	0.097	0.093	0.448	-0.223	0.226	54.78%	0.497
	Indicated	-0.048	0.090	0.095	0.445	-0.211	0.220	54.57%	0.498
Explainability	No Explainability	-0.046	0.099	0.102	0.460	-0.210	0.226	47.84%	0.499
	Low Explainability	-0.040	0.087	0.092	0.472	-0.223	0.219	56.56%	0.495
	High Explainability	-0.047	0.093	0.087	0.400	-0.221	0.222	60.27%	0.489

3.4.2 The Effect of Recommendation Characteristics on Recommendation Adoption (H1-H3)

This subsequent analysis phase was designed to assess the effects of various recommendation characteristics on the likelihood of adoption. Three specific aspects were examined: recommendation convergence, the presence of a source indication, and the degree of explainability, which correspond to H1, H2, and H3, respectively. Logistic regression analysis supports H1, confirming that recommendation convergence significantly increases the likelihood of recommendation adoption by 5.2 times (Odds ratio = 5.207, $p < .0001$). However, H2 did not receive empirical support; the presence of source indication did not significantly influence adoption rates, as indicated by the non-significant logistic regression outcome (Odds ratio = 0.984, $p = 0.8328$). H3 posited that users would adopt recommendations more frequently when accompanied by higher levels of explainability. While the logistic regression results using the Wald test did demonstrate a statistically significant effect of explainability on recommendation adoption ($R^2 = 0.0116$, $p < .0001$), the modest R^2 value suggests that the practical impact of explainability, though significant, may be limited in scope.

The pairwise comparison test conducted to evaluate the influence of different levels of explainability on the likelihood of recommendation adoption yielded statistically significant results. The analysis demonstrated that recommendations were more likely to be adopted under conditions of high explainability compared to conditions of no explainability (estimate = -0.5281, $p < 0.0001$). Further, recommendations adoption rates were higher in the low explainability conditions compared to the condition of no explainability (estimate = -0.3633, $p = 0.0003$). These findings strongly support H3. The results indicate a clear preference for recommendations accompanied by a high level of explainability.

3.4.3 The Mediating Effect of Cognitive Load on Recommendation Adoption (H4)

The mediation analysis conducted to investigate the proposed H4a, H4b, and H4c revealed non-significant indirect effects, thus not supporting the hypothesized mediation roles. For H4a, the cognitive load's mediating effect on the impact of convergent recommendations on adoption was not significant ($b = 0,0003$, $p = 0,678$). Similarly, H4b postulating mediation of cognitive load via the presence of the source indication on adoption also did not achieve statistical significance ($b = -0,0171$, $p = 0,934$). Finally, H4c that higher explainability in AI recommendation systems would increase cognitive load and subsequently increase adoption was not supported ($b = -0,0092$, $p = 0,178$). These findings were consistent across models with both raw and log-transformed pupil sizes, indicating that neither transformation affected the mediation outcome. Therefore, it can be concluded that H4a, H4b, and H4c are not supported by the data.

Although the mediation analysis did not yield significant results for the hypothesized mediation pathways of cognitive load, noteworthy findings emerged from the linear and logistic regression analyses. Specifically, the presence of source indication was associated with a higher cognitive load ($b = 0.0129$, $p = 0.0008$). Conversely, recommendations were associated with a lower cognitive load when they were convergent ($b = -0.204$, $p < 0.0001$). Furthermore, a higher cognitive load was found to decrease the likelihood of recommendation adoption ($OR = 0.911$, $p = 0.0492$).

3.4.4 The Mediating Role of Emotional Affect on Recommendation Adoption (H5)

A mediation analysis was also performed to assess the mediating effects of emotional state on the adoption of recommendations, as hypothesized in H5a and H5b. The results indicate that the indirect effects were non-significant for both hypotheses. For H5a, which suggested that a negative emotional state mediated by divergent recommendations would lead to lower adoption rates, the effects were not significant across measures of valence and arousal. Similarly, H5b's proposition that positive emotions elicited by AI systems with high explainability would increase adoption did not find statistical support. These outcomes were consistent irrespective of the emotional measurement model employed, leading to the conclusion that the data do not support the mediating role of emotional state as proposed in H5a and H5b.

Despite the non-significant findings regarding the mediating effects of emotional state on recommendation adoption, subsequent logistic and linear regression analyses revealed several significant partial effects. The analyses indicated that emotional valence was slightly but significantly reduced when a source was indicated, compared to when it was not ($b = -0.00577$, $p = 0.0376$). Moreover, convergent recommendations were found to be associated with a lower emotional valence ($b = -0.331$, $p < 0.0001$). Additionally, convergent recommendations were linked to a decrease in arousal levels ($b = -0.2813$, $p = 0.0002$), indicating less emotional excitement in response to these recommendations.

3.5 Discussion

This study's findings demonstrate that convergence in recommendations increases the probability of their acceptance (H1). Contrary to expectations, the indication of the recommendation's source did not amplify the rate at which expert recommendations were adopted (H2). Furthermore, a clear correlation was observed where greater explainability in AI-driven recommendations significantly fostered their adoption (H3). The analysis did not support the hypothesized mediating function of cognitive load (H4) or emotional affect (H5) in the acceptance of recommendations. Nonetheless, other relationships were unveiled. Specifically, the presence of source indication resulted in elevated cognitive load, whereas convergent recommendations reduced cognitive load. Further, an increased cognitive load was inversely related to the likelihood of recommendation adoption. Emotional valence was observed to diminish when the source of a recommendation was indicated, as opposed to instances where it was not indicated. Moreover, convergent recommendations elicited lower emotional valence, coupled with lower arousal levels, suggesting a less happy and excited emotional response to such recommendations.

3.5.1 Theoretical Contributions

This study has many theoretical contributions. This research addresses the gap in the scholarly literature on user response to simultaneous recommendations from dual sources—namely, an AI RS and expert-driven recommendations. Prior research has not explored user processing behaviors in scenarios where they are confronted with convergent or divergent advice from these two distinct sources. This study elucidates that users are more likely to adopt recommendations when there is a consensus between AI and expert guidance, that is when the recommendations converge, as opposed to when the recommendations are at odds. By doing so, the researchers enrich the body of knowledge which previously did not compare the influence of these two recommendation sources, nor understand user reactions to the simultaneous presentation of these sources of advice.

In line with existing studies (Adomavicius & Tuzhilin, 2005; Cramer et al., 2008; Rzepka & Berger, 2018; Sinha & Swearingen, 2002; Wang & Benbasat, 2007; Zanker, 2012) this study strongly supports and confirms the importance of explainability in AI RS and the notion that transparency and understanding of the recommendation process significantly influence user adoption. The preference for highly explainable recommendations underscores the importance of clarity and openness in AI systems, emphasizing that users value understanding the rationale behind recommendations.

This study shows that the presence of the source indications increased cognitive load. This is in line with previous studies suggesting that consumers engage in dual processing—both heuristic and systematic—in online decision-making (Chen & Chaiken, 1999; Koh & Sundar, 2007; Koh & Sundar, 2010). The source labels serve as cues that activate the expertise heuristic; however, they subsequently prompt systematic processing (Koh & Sundar, 2010). When users encounter source indications such as "Powered by AI" and "Editor's Pick," they are compelled to process not only the content of the recommendation itself but also the implications of the source labels. This additional processing requires additional cognitive effort as users attempt to interpret the credibility and authority implied by the labels and reconcile this with their own perceptions and knowledge.

This study demonstrates that convergent recommendations, being in agreement, lead to a lower cognitive load compared to divergent recommendations that present conflicting information, thereby requiring more mental effort to resolve. This aligns with the findings of Xu et al. (2020), who observed a significant increase in cognitive strain when participants were presented with divergent advice. The study's context, involving a mix of AI recommender systems and expert inputs (Pfeiffer & Benbasat, 2012) presents a complex information environment when the advice from both sources is opposite, hence increasing cognitive load.

This study presents findings that challenge established theories regarding cognitive load and decision-making. Contrary to previous research suggesting that an increase in cognitive load can lead to a higher likelihood of adopting recommendations due to a reliance on intuitive judgment, this study found an inverse relationship. Earlier studies based on the adaptive decision-maker model posited that consumers overloaded with information would likely exhibit low reactance and accept product recommendations to manage cognitive strain (Aljukhadar et al., 2012; Bettman et al., 1990). This acceptance was thought to stem from a depletion of cognitive resources, causing a shift towards intuitive reasoning over deliberate processing (Pocheptsova et al., 2009). Recommendations, whether AI-driven or expert-based, are seen as tools that simplify the decision-making process by acting as a heuristic during periods of high cognitive load (Aljukhadar et al., 2012; Häubl & Trifts, 2000). However, this study's findings suggest that as cognitive load increases, the likelihood of adopting recommendations decreases, providing a novel perspective on how cognitive load impacts consumer behavior in the context of online recommendations. This may be explained by the fact that a high cognitive load can also be exacerbated by an abundance of choices or conflicting information. This can lead to the paradox of choice, where too many options or too much information can lead to anxiety, paralysis of analysis, or a lower likelihood of making any decision (Schwartz, 2004). Further, another explanation for this may be that with a high cognitive load, individuals may become more skeptical of the information provided. If the effort required to verify the trustworthiness of the recommendation is too high, users might default to a cautious approach and thus be less likely to accept the recommendation (Tiedens & Linton, 2001).

Moreover, the researchers demonstrated that convergent recommendations elicited lower emotional valence, coupled with lower arousal levels, suggesting a less happy and excited emotional response to such recommendations. This may be explained by the fact that the reduced emotional intensity could signal a perceived lower need for careful, analytical processing of the recommendations, as there is less perceived risk or uncertainty involved. Also, this research found that emotional valence was observed to diminish when the source of a recommendation was indicated, as opposed to instances where it was not indicated. This may be explained by the fact that if the source of the recommendation is known, recipients may perceive potential biases or doubt the expertise of the source, leading to skepticism that reduces the positivity of their emotional response. The awareness of the recommender's possible agenda or interests can create caution and decrease positive emotions. Furthermore, people often use heuristic cues such as the authority of a source to evaluate the value of information (Cialdini & Goldstein, 2004). If the disclosed source is not viewed as an authority or if the recommendation contradicts an individual's established beliefs about authoritative sources, the emotional response may lean towards the negative.

3.5.2 Managerial Implications

This study has several managerial implications. To begin, results revealed that users are more inclined to adopt recommendations when AI and expert advice converge. For managers, this finding suggests the importance of integrating AI systems with expert input in their decision-making tools. By ensuring that AI recommendations are aligned with expert advice, businesses can enhance the effectiveness of their recommendation systems, thus increasing user trust and adoption rates. Individuals generally prefer to minimize uncertainty and mitigate risk while making decisions. Therefore, online retailers should integrate various sources of recommendations within their websites. This approach enables customers to feel more confident when they encounter consistent advice from several sources, leading to reduced uncertainty. It is important to note that retailers should not falsely engineer the consistency of these recommendations. Moreover, the benefit of convergent recommendations is not attainable if a website only offers advice from one source (Xu et al., 2020).

The study confirms the significance of explainability in AI RS. Transparency and understanding of the recommendation process are crucial in influencing user adoption. This highlights the necessity for managers to prioritize the development of AI systems that are not only accurate but also transparent and understandable to users. Moreover, offering detailed explanations of how AI recommendations are generated could differentiate a business in a competitive market where customers are increasingly concerned about the workings of AI.

The study indicates that convergent recommendations reduce cognitive load compared to divergent advice. From a managerial perspective, it is crucial to design recommendation interfaces in a way that minimizes cognitive load. This can be achieved by providing clear, consistent, and aligned recommendations from both AI and human experts. Again, it is not advised in any case that managers manipulate the alignment of these recommendations. Additionally, the inverse relationship found between cognitive load and the likelihood of adopting recommendations suggests a need to simplify decision-making processes for users. Managers should aim to design user interfaces and recommendation processes that are intuitive and easy to navigate.

3.5.3 Limitations and Future Research

As is the case with all empirical research, this study is subject to certain limitations. A primary limitation encountered was the design of the study, which involved participants interacting with a simulated movie recommendation system and streaming platform. Participants were under the impression that the system was adapting to their preferences to offer personalized movie suggestions. However, due to the scope of this project, it was infeasible to develop a fully operational system; thus, the recommendations were identical for all participants. This design choice may have influenced participants' perceptions of the system's personalization capabilities, potentially altering their engagement with the recommendations provided. This highlights the need for future research to implement a more sophisticated system capable of generating genuine personalized recommendations. Furthermore, participant fatigue is a factor that cannot be discounted, given that each subject was required to evaluate 120 movies. It was observed that decision times decreased progressively, with decisions towards the end of the sequence tending towards a more reflexive rather than reflective nature. This pattern suggests that participants may have increasingly relied on heuristic processing of the movie posters, as opposed to engaging with the accompanying recommendations. This behavioral change could have implications for the interpretation of the data. In addition, the sample of movies used in this study was specifically selected to minimize pre-existing attitudes among participants by focusing on unpopular, unknown, or older films. This selection was pre-tested with a small group to ensure that participants were not overly familiar with the movies, which aligns with the study's younger sample demographic. However, this choice may introduce some concerns about external and predictive validity. Since the movies were chosen to suit a younger audience, it may not fully represent the preferences or familiarity levels of a more diverse, general population. This could affect the generalizability of the findings, as movie preferences and recognition might differ across age groups and cultural backgrounds. Furthermore, the predictive validity of the study could be influenced if the same level of unfamiliarity with the movies does not hold true for older or more diverse samples, potentially limiting how well these findings apply to broader consumer behavior in real-world scenarios. Future research could consider a more representative range of movies to improve external validity and ensure the results are applicable across different demographics. Further, the current literature on cognitive load provided a theoretical basis for several hypotheses within this study. Nevertheless, it remains uncertain whether the tasks completed by participants can be categorized as highly cognitively demanding. The tasks were relatively straightforward and required participants to consider only a limited amount of information, which diverges from scenarios in established studies where subjects had to process extensive information. In the context of experience goods, such as movies, the impact of recommendations on cognitive load is not straightforward. Unlike search goods, for example computers, which feature numerous quantifiable attributes leading to potential information overload, experience goods typically involve fewer, more subjective attributes. Consequently, whether a recommendation increases or decreases cognitive load may depend significantly on the alignment between the recommendation and the consumer's pre-existing preferences. For example, if a recommendation contradicts a consumer’s initial opinion about a product, it could increase cognitive load as the consumer processes this conflicting information. Conversely, if the recommendation aligns with their pre-existing views, it may simplify decision-making and reduce cognitive load. However, in the case of movies, which are inherently difficult to evaluate before consumption, it is unclear how a recommendation could affect cognitive load. This highlights the need for further research into how recommendations impact cognitive load across various types of goods, raising questions about the broader applicability of the findings. In addition, in this study, researchers only investigated the effect of a single independent variable on recommendation adoption. Regarding the interplay of recommendation convergence, the presence of source indication, and the level of explainability, it is recommended that future studies investigate the joint effects of these three independent variables. Such an investigation could highlight the optimal configuration that provides the best user experience and leads to better recommendation acceptance. Another limitation of the study is that the distinction between low and high explainability was determined qualitatively, without the use of manipulation checks or pretesting to establish these levels quantitatively. This qualitative approach may introduce subjectivity, as it relies on theoretical constructs rather than empirical validation. This limits the ability to generalize the findings based on specific thresholds of explainability. Future research could address this by implementing manipulation checks or pretesting to create more clearly defined levels of explainability. Lastly, this study was conducted with a focus on low-involvement products, specifically movies, which are generally associated with lower perceived risk. Hence, the decision-making process of participants may not reflect the complexities involved in high-stakes or high-involvement contexts. Future research should extend this evaluation to various product categories, especially those with higher involvement and risk. This expansion would offer insights into consumer decision-making processes in scenarios where the consequences of their choices are more significant and provide a better understanding of how users react to dual recommendations in such settings.

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Chapter 4: Conclusion

With the growth of online information and the expansion of e-commerce, an increasing number of e-tailers are integrating recommender systems into their platforms. This trend is evolving; businesses are progressively adopting a hybrid approach by combining algorithmic and expert recommendations. This combination aims to optimize customer experiences by merging data-driven suggestions with human expertise. The present thesis aims to explore how this integration of information from dual recommendation sources influences consumers' behavior to adhere to these recommendations. More specifically, this study aims to identify the extent to which certain attributes of recommendations - namely, convergence, source indication, and explainability - impact users' acceptance of advice coming from both AI-based systems and experts. Furthermore, this research aims to explore the mediating roles of cognitive load and emotional state in the process of accepting these recommendations. Chapter 2 of this thesis presented a literature review that offers an insight into the current state of research surrounding AI-based recommender systems and expert recommendations. In the goal of understanding the impact of the integration of dual recommendation sources on consumer behavior, the empirical experiment detailed in Chapter 3 was conducted to address the research questions. The independent variables in this study, which encompass convergence (either convergent or divergent), source labeling (either disclosed or undisclosed), and varying levels of explainability (none, low, or high), were methodically manipulated to assess their effects on recommendation acceptance.

This final chapter summarizes the methodology employed by this thesis to examine the above-mentioned manipulations. Subsequently, it revisits the research questions and the results derived from the study. Finally, the chapter delves into discussing both the theoretical and managerial implications that emerge from this thesis.

4.1 Laboratory Experiment

The study utilized a 2x3x3 within-subject factorial design to assess the impact of recommendation sources and recommendation attributes on users' physiological responses and decision-making behavior. The independent variables in this study, which encompass convergence at two levels (either convergent or divergent), source labeling at two levels (either disclosed or undisclosed), and explainability at three levels (none, low, or high), were methodically manipulated to assess their effects on recommendation acceptance. Participants interacted with a simulated movie streaming platform, believing it to be an AI system learning their preferences to provide personalized movie recommendations. Initially, participants set up an account and rated ten movies to inform the AI of their preferences. They also selected their favorite genres from a list. During the experiment, participants viewed a movie poster and received two recommendations for each: one from the AI and one from experts. They then chose to either add the movie to their watchlist or not, without a time constraint. Participants each had 120 trials, presenting a different movie with every trial.

The study utilized a comprehensive setup to gather physiological measurements. Cognitive effort was measured by observing changes in pupil diameter, comparing the task-induced pupil size to the baseline for each subject and event. Emotional reactions were captured using Facereader for facial expressions, and phasic electrodermal activity to determine arousal levels. Behavioral outcomes were assessed by tracking participants' choices to add movies to their watchlist and their adherence to the recommendations provided.

4.2 Reminder of the Research Questions and Main Findings

As the study concludes, it is pertinent to revisit the research questions that guided this investigation and to reflect upon the key findings that have emerged. The objective of this research was to answer the following two questions:

1. To what extent do the characteristics of recommendations influence their adoption when users receive simultaneous recommendations from AI-based systems and human experts? With specific attention to:

- *a) Recommendation convergence*
- *b) The presence of a source indication*
- *c) The level of explainability*

2. Are there mediating mechanisms through which physiological factors influence the relationship between recommendation characteristics and the adoption of the recommendation? Specifically, this study seeks to elucidate the roles of:

- *a) Cognitive load: How does the cognitive load imposed by recommendation characteristics affect recommendation adoption?*
- *b) Emotional state: How does the emotional state (valence and arousal) resulting from recommendation characteristics affect recommendation adoption?*

In addressing the primary research question, it has been demonstrated that recommendation convergence significantly increases the likelihood that users will adopt the recommendations. This suggests a synergy effect when AI-based systems and experts provide the same suggestion, enhancing user confidence in the recommended choice. Contrastingly, the presence of a source indication does not significantly affect the adoption rates. Whether a recommendation is explicitly identified as coming from an AI or expert source does not appear to play a crucial role in the decision-making process for users within the context of this study. Lastly, the level of explainability emerges as an influential factor. Recommendations that are accompanied by a higher level of explainability, offering users a clearer understanding of the rationale behind the suggestion, are more likely to be adopted. This reflects a user preference for transparency in recommendation systems, demonstrating that users value understanding the reasoning underlying the recommendations.

In answering the second research question, the analysis did not provide evidence that cognitive load or emotional state serve as mediators in this relationship. Specifically, neither the cognitive load associated with the recommendation characteristics, nor the emotional responses elicited—encompassing both the valence and arousal—were shown to have a mediating effect on the likelihood of recommendation adoption. However, there were notable direct associations. The presence of source indications corresponded with an increase in cognitive load, whereas convergent recommendations were linked to a decrease in cognitive load. Furthermore, it was observed that an increase in cognitive load corresponded with a decrease in the likelihood to adopt recommendations. From an emotional perspective, source indications led to a slight reduction in emotional valence, indicating a less positive emotional response. Additionally, convergent recommendations resulted in lower levels of both valence and arousal, suggesting a calmer emotional state in response to these recommendations. These findings suggest that while the mediating roles of cognitive load and emotional state were not supported, these factors still have a direct and significant impact on user interactions with online recommendations.

4.3 Theoretical Contributions

This research makes significant theoretical contributions by addressing a gap in the literature concerning how users respond to simultaneous recommendations from AI systems and human experts. The study began with a thorough literature review to evaluate the current research and identify gaps related to online recommendations, particularly those involving AI and human expert advice. The review pinpointed several areas needing further investigation. A primary gap was user response to simultaneous advice from these two sources in digital environments. Additionally, insights into user behavior when confronted with conflicting advice were scarce, and the methods users employ to assimilate and reconcile such contradictions were underexplored. The literature also showed inconsistent preferences for AI versus human advice, indicating context-dependent decisions. Moreover, the optimal level of explainability in AI systems, particularly its impact on cognitive load and comprehension, remains underexplored. These findings demonstrate the need for more research to enhance recommendations and improve user decision-making in digital contexts.

The empirical study advances the understanding of user responses to AI-driven and expert recommendations by identifying how users process simultaneous advice that is either convergent or divergent. Consistent with earlier studies (Xu et al., 2020), findings suggest users prefer convergent recommendations from AI and experts. Hence, they are more likely to adopt recommendations when both sources align in their advice. Findings reveal that explainability plays an important role in recommendation adoption, as was also demonstrated by previous research (Adomavicius & Tuzhilin, 2005; Cramer et al., 2008; Rzepka & Berger, 2018; Sinha & Swearingen, 2002; Wang & Benbasat, 2007; Zanker, 2012). Indeed, users are more likely to accept advice when they understand the reasoning behind it, and high explainability was shown to lead to the highest recommendation adoption rate. The research also indicates that source labels on recommendations increase cognitive load. Further, while convergent recommendations lower cognitive load, divergent ones increase it, possibly due to the challenge of reconciling conflicting advice. Contrary to earlier studies (Aljukhadar et al., 2012; Bettman et al., 1990), this study demonstrates that an increase in cognitive load decreases the likelihood of adopting recommendations. Lastly, the research showed that convergent recommendations led to a lower emotional response, that is lower emotional arousal and more negative valence. Additionally, the display of the source label tended to decrease emotional valence.

4.4 Managerial Implications

The findings of this study have significant implications for the way businesses use AI and expert recommendations. Users show a preference for recommendations when there's agreement between AI algorithms and human expertise. This underscores the importance for managers to integrate both sources into their systems to improve the credibility of their recommendations, leading to higher adoption rates. E-tailers, specifically, should offer recommendations from various sources on their platforms, as this multi-source approach tends to build consumer confidence and decrease their decision-making uncertainty. The research also highlights the critical role of transparency and explainability in AI systems. Companies that invest in making their AI recommendations clear and understandable can gain a competitive edge as users are looking for systems they can understand and rely on. Furthermore, the study suggests that when users are presented with convergent recommendations from AI and experts, their cognitive load is reduced, making it easier for them to make decisions. Hence, it is important for managers to create interfaces that are straightforward and facilitate easy navigation and decision-making, and this, without manipulating the recommendation process.

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